Detection of Ball Spin Direction using Hitting Sound in Tennis

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Abstract: This paper describes the detection of rotation direction using the hitting sound of tennis balls. Since each ball rotation direction has a slightly different rotation direction and trajectory, there should be a difference in the hitting sound. To distinguish the characteristics of ball rotation direction, a database was constructed that combines the hitting sound recorded experimentally with ball rotation direction. Since it is difficult to distinguish audible differences in hitting sounds by ear, it is necessary to identify them using measuring instruments. For this purpose, after extracting the amplitude spectrum by fast Fourier transform of the shot sound, the entire data was normalized and classified by a support vector machine. As a result of evaluating this method, a high accuracy was obtained in identifying the sound associated with *slice* among other hit sounds. The proposed method also evaluated the ball hit sound from a YouTube video in an unknown environment and achieved a perfectly correct identification of *spin* and *slice*.

1 INTRODUCTION

In recent years, there has been a growing movement worldwide to introduce science and technology into sports. Smart courts (SecondSpetrum, 2020; Playsight, 2020), which have multiple cameras that can track the movement of players and balls using computer vision technology, are utilized in various sports such as football, basketball, and so on (Seo et al., 2018). The smart court system developed to improve the accuracy of umpire decisions in tennis introduced "Hawkeye" which includes eight super high-speed cameras to specify the trajectory and landing point of the ball (Baodon, 2014) to inform umpires in professional matches and to smoothly advance games. However, smart courts require large systems to be installed and their cost prohibit personal use. Form (pose) analysis is an important issue in computer vision for sports in which many studies have been reported (Cust et al., 2019; Appelbaum and Erickson, 2018; Okamoto et al., 2015; Cao et al., 2019). Such studies have achieved significant progress in many sports, but one important issue has not been studied well in ball games – the detection of the spin (or rotation) direction of balls.

Figure 1: Smartsensor can be attached to the grip end of the racket and can measure the rotation direction, speed, rotational speed, etc. of the stroke.

The trajectory of a ball is greatly affected by its rotation, so players need to be able to detect the rotation direction to predict the ball trajectory. In tennis especially, players need to be able to perform balls with various rotation and also identify the rotation direction of the opponents' balls. A smart tennis sensor (Zepp, 2020) has been developed to measure ball speed, rotation direction and revolution using an accelerometer and three-axis gyro-sensor, which is usually attached to the grip-end of the racket (Figure 1).

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Players can learn to hit various rotation directions by using smart tennis sensors, but they do not provide information about the opponent's treatment of the ball. Ball rotation can be detected using a high-speed and high-resolution camera, but since tennis is a sport in which the balls travel fast in a short period of time, and are hit at various places in the court, a precise tracking system is required in addition.

Since tennis players are known to make decisions based on the hitting sound of the opponent, in this study, we focused on the hitting sound. Although some previous studies focused on the hitting sound of tennis balls during play, they paid attention only to ball speed (Zhang et al., 2017). In depth research on hitting sound and ball rotation direction has not been previously conducted. However, Canal-Bruland et al asked subjects to watch a professional tennis match on video and predict the trajectory of the ball at that time (Canal-Bruland, 2018). As a result, it was shown that the hitting sound could be an important factor in predicting the ball trajectory. In predicting the trajectory of a ball, three types of the rotation direction, namely *spin*, *flat*, and *slice* form the basis of ball movement pattern. By recognizing rotation direction, a rough trajectory of the ball can be predicted, and player performance can improve as prediction accuracy improves.

A *spin* hit happens when the head of the racket is rotated over the top of the ball during a hit causing a tangential velocity of the top of the ball in the same direction as the ball's trajectory resulting in lower drag force at the bottom of the ball so it falls downwards (Figure 2a). A flat hit ball does not spin to any significant degree so does not veer from the direction in which it is hit (Figure 2b). A slice hit, contrary to *spin*, happens when a player angles the racket back and slides it underneath the ball when hitting which makes it veer upwards. The tangential velocity of the top of the ball is in the opposite direction of the trajectory of the ball, so the force of this hit tends to be weaker than *spin* or *flat*. Players may also make the ball deflect left or right by corresponding rotations (Figure 2c). To validate the proposed method, a set of tests was, performed to obtain necessary ball hitting sound data. Then, a identifiable data set was constructed using a developed identifier. Thereafter, accuracy of the identifier was evaluated. Finally, we sampled ball hitting sounds from YouTube and applied the identifier to observe the percentage of correct answers.

Following, Section 2 describes related research, Section 3 describes the database constructed, Section 4 proposes a method for processing the data, and Section 5 describes the results and considerations of evaluation experiments using the proposed method.

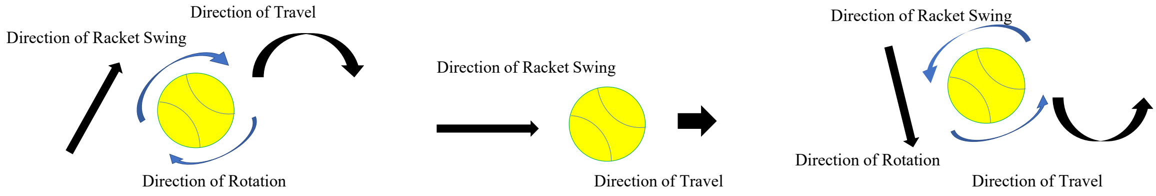
2 RELATED RESEARCH

To improve player performance in tennis, Asano et al. attached markers to a ball and used high-speed cameras to determine the rotation angle and number of rotations for each of three axes. Three-dimensional location of the ball center was obtained from the camera parameters with two cameras, and the ball trajectory was estimated.

Elsewhere, research has focused on the sound of hitting balls in sound table tennis. A game was designed for blind people with a rule that if no returned ball hitting sound was heard, it was a foul. Because the judge only relied on hearing, application of the rule was ambiguous. Kogusuri et al. aimed to clarify this rule (Kogusuri et al., 2008). In that research, they propose a technique to determine a hit by focusing on frequency domain components by recording the hit sound with a digital audio tape recorder via a noise meter, applying wavelet transform analysis, and using the hit sound. Similar concept was used aimed at improving the player performance in other ball sports studies focusing on the hitting sound. Although the effect of ball hitting sound on performance has been studied, waveform characteristics of the hitting sound have not been clarified.

Therefore, Zhang et al. are conducting research of the latent characteristics of the hitting sounds of opponent players (Zhang et al., 2017). In their study, the sound of hitting a service ball was extracted from the deuce side and the advantage side in 15 examples each, and the characteristics were compared by overlapping the time domain waveforms. Specifically, a television image was recorded and its sound was extracted, the first peak of each sound waveform was overlapped and compared for each player, and the sound characteristics of each player were detected from the average amplitude of the first peak and the arrival time between the first peak and the last peak. It is defined that a sample point has a peak when it has a greater value than two adjacent sample points and a certain threshold. It is how to find peaks. They reported a correlation between ball speed and hitting sound magnitude, but rotation direction was not mentioned.

Hitting sound has been studied in other sports. However, in tennis, although some studies aimed at improving performance focused on the sound of hitting balls, no study has been conducted to determine ball rotation from the sound of hitting balls as far as we know. In this study, we focused on ball hitting



(a) *Spin* rotation direction. (b) *Flat* rotation direction. (c) *Slice* rotation direction.

Figure 2: Three types of rotational directions.

sound to describe and identify rotation direction.

3 METHODS AND CONSTRUCTION OF BALL HITTING SOUND DATABASE

This section describes experiments to construct a hitting sound database, and processing algorithm to construct a hitting sound pattern database from collected sound data.

3.1 Recording Exercise

The purpose of this exercise was to record *spin*, *flat*, and *slice* shot sounds and create a basic pattern data set to identify rotation directions. The recording was performed under the following conditions.

- Date & Time: 2019/12/10 11:00-13:00
- Place: Ninomiya Park Tennis Court (hard court, outdoor), Tsukuba City, Japan
- Weather: Sunny & almost no wind
- Hitter: A male, 15 years of tennis experience

Figure 3 illustrates the experimental setting, and Table 1 shows specifications of the equipment used in the recording. The hitting procedure is controlled to maintain the quality of recorded sounds as follows:

1. A ball person throws a ball for a hitter.
2. The hitter hits the ball with a certain direction and force which is decided by the hitter.
3. The hitter tells a recorder the rotation direction (and force) that the hitter decided.

In total, 92 trials were performed.

3.2 Ball Hitting Sound Database Construction

For each recorded sound, a 50 ms clip was extracted so that each clip can include the moment of impact. This was manually done for all 92 recorded sound data using Audacity. We, thus, collected a ball hitting pattern dataset consisting of 92 sound clips and the corresponding rotation direction.

Table 1: Equipment used in the recording.

Equipment	Description
Microphone type	TAMAGO-03
Microphone position	2 near the pillars connected straight to PC
Tennis ball	20 new balls
Racket	SRIXON REVO CV3.0 (SR21802)
PC	16 kHz and 16-bit recording

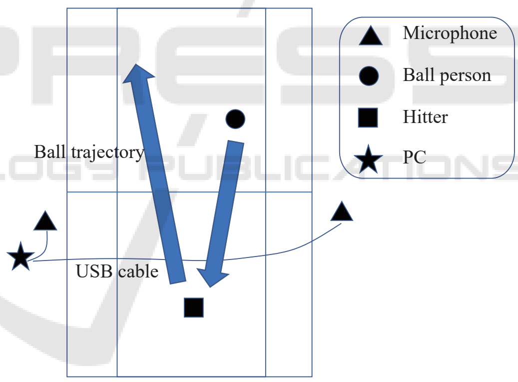


Figure 3: Experimental setup. A ball person throws a ball, and a hitter hits the ball. Arrows show a typical trajectory of the ball for a single trial.

4 PROPOSED METHOD

This section explains the proposed method to identify rotation direction from hitting sound. The proposed method uses frequency analysis, data normalization, dimensionality reduction, and 2-class SVM to classify the ball rotation (Figure 4).

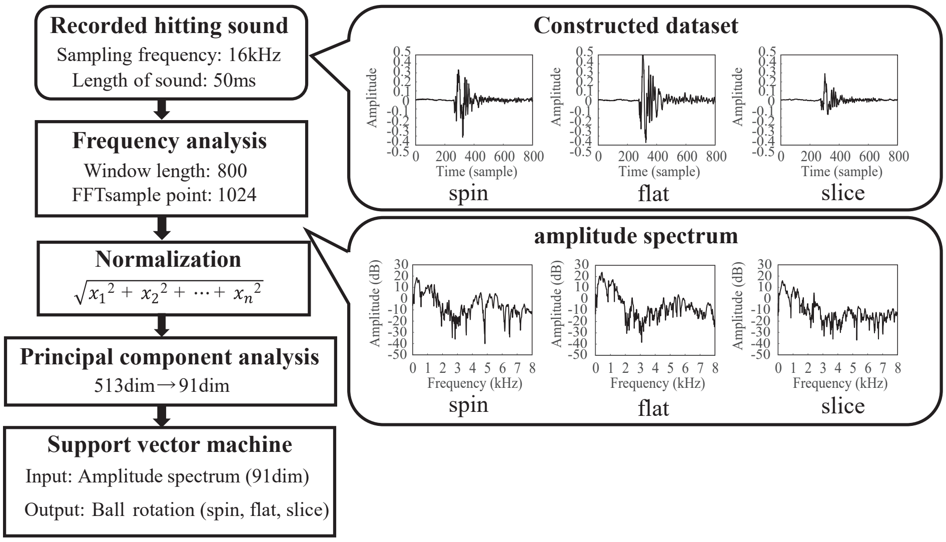


Figure 4: Flowchart of the proposed method.

4.1 Frequency Analysis

The input sound pattern is assumed to have 50 ms duration including the impact of hitting as described in Section 3. Fourier transform is performed for the input signal. Fourier transform is a frequency analysis method used to decompose a complex sound into its constituent parts, and there is an algorithm to greatly increase the speed of the discrete Fourier transform, which is called fast Fourier transform (FFT). FFT is beneficial when dealing with a large amount of data, and thus we decided to use FFT with a rectangular window for frequency analysis. In the present case, the number of data sets to be processed was 92. Since the sampling frequency was set at 16 kHz and the time component of clipped signals was 50 ms, the length of the signal was 800 samples. For FFT, the window length of 1024 samples with zero padding was adopted. When FFT is applied, the real part of the frequency-amplitude diagram is line-symmetric, the imaginary part is point-symmetric, that is, it is conjugate, and the amplitude spectrum is line-symmetric. Therefore, the frequency component of interest at this time was 0–8 kHz (Nyquist frequency). Thus, the number of dimensions of the data to be treated this time was 513 dimensions. The analysis was performed using MATLAB.

4.2 Data Normalization

Normalization was performed to prevent variation due to the difference of the impacted position for each data.

4.3 Dimensionality Reduction with Principal Component Analysis

Since only 92 samples with a 513 dimensional feature representation for each impact sound were obtained, the training samples should be mapped to the lower dimensional feature space to ensure good generalization performance. Principal component analysis (PCA) (Diamantaras and Kung, 1998) estimates principal components of a dataset, where a principal component with a larger score gives better representation of the dataset. By selecting principal components with larger scores, the dataset is well represented with a lower dimensional feature space. Therefore, we applied the Principal Component Analysis (PCA) to our impact sound data. The procedure of PCA is described as follows. Let $\mathbf{x}_i$ $(i = 1, \ldots, N)$ represent the i-th D-dimensional data. The DC offset is first removed by,

$$\tilde{\mathbf{x}}_i = \mathbf{x}_i - \frac{1}{N}\sum_{j=1}^{N}(\mathbf{x}_j). \tag{1}$$

DC offset is the addition of a Direct Current component to a device's performance and the effect of surrounding electrical influences that causes it to deviate from 0V.

The covariance matrix of $\mathbf{X}$ is, then, calculated as,

$$\Sigma_{\mathbf{X}} = \frac{1}{N}\sum_{i=1}^{N}\tilde{\mathbf{x}}_i\tilde{\mathbf{x}}_i^T. \tag{2}$$

Eigenvalue decomposition is performed for the obtained covariance matrix $\mathbf{X}$ by,

$$\Sigma_{\mathbf{X}}\mathbf{U} = \mathbf{U}\Lambda, (\mathbf{U}^T\mathbf{U} = \mathbf{I}), \tag{3}$$

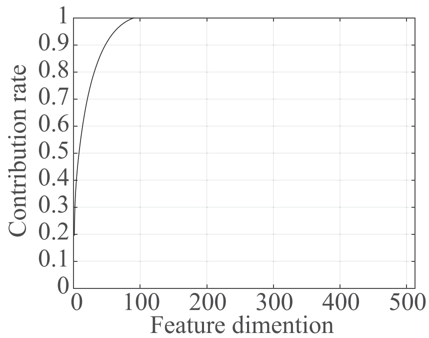


Figure 5: Cumulative contribution rates of PCA for the constructed database. The horizontal axis is the dimension of rotation direction and the vertical axis is the cumulative contribution rate at the selected feature dimension.

where $\mathbf{U}$ is the square $D \times D$ matrix whose i-th column is the eigenvector, and Λ is the diagonal matrix whose diagonal elements are the corresponding eigenvalues.

Figure 5 shows a cumulative contribution rate for first 91 principal components in the descending order. Since the cumulative contribution rate reached 1 with the 91 principal components, the number of dimensions was set to 91 in the feature vector for identification. Note that due to rank deficient, the rate reached 1 with 91 principal components for 92 samples. In Figure 5, the rate also reached 0.7 with 20 principal components, and we will also verify a lower feature such as a 20-dimensional feature in the evaluation.

4.4 SVM

The proposed method performs two-class classification. For example, when a target is *spin*, the identification is to discriminate whether the sound is for *spin* or not. This means that three types of two-class identification, that is, for *spin*, *flat*, and *slice* were performed.

For the low dimensional input vector, $\mathbf{s}$, obtained by PCA, we first introduce a general classification function, y, defined as,

$$y = \mathrm{sign}\left(\mathbf{w}^T \mathbf{s} - h\right), \tag{4}$$

where $\mathbf{w}$ indicates a weight vector for the input and h is a threshold. Function $\mathbf{sign}(u)$ is a sign function, which outputs 1 when $u > 0$ and outputs -1 when $u \leq 0$. In other words, Eq. (4) separates a space represented by $\mathbf{s}$ into two sub-spaces using a separating hyperplane defined by $\mathbf{w}$. An SVM (Scholkopf et al., 1999; Vapnik, 1998) is a method to determine the separating hyperplane that maximizes the distance (margin) between the separating hyperplane and the nearest sample. However, in a conventional SVM, all input samples should be linear separable, which is defined by,

$$(\mathbf{w}^T \mathbf{s}_i - h) \cdot t_i \geq 1, \; i = 1, \ldots, N, \tag{5}$$

where t_i shows the correct class label (1 or -1) for $\mathbf{s}_i$. $\mathbf{s}_i$ stands for the i-th input vector.

This means that the samples are separated by two hyperplanes such as

$$H1 \;:\; \mathbf{w}^T \mathbf{s}_i - h = 1, \tag{6}$$
$$H2 \;:\; \mathbf{w}^T \mathbf{s}_i - h = -1, \tag{7}$$

and there are no samples between these two hyperplanes. The distance between the separating hyperplane and each of these hyperplanes is defined as $1/\|\mathbf{w}\|$.

To relax a linear separable constraint, a soft-margin is introduced to SVM, which allows training samples between $H1$ and $H2$. For this, a distance parameter ξ_i for $\mathbf{s}_i$ is introduced. It is defined for the i-th sample with $t_i = 1$ as,

$$\xi_i = \begin{cases} -\mathbf{w}^T \mathbf{s}_i + h + 1 & (\mathbf{w}^T \mathbf{s}_i - h < 1) \\ 0 & (otherwise) \end{cases} \tag{8}$$

It is also defined for the i-th sample with $t_i = -1$ as,

$$\xi_i = \begin{cases} \mathbf{w}^T \mathbf{s}_i - h + 1 & (\mathbf{w}^T \mathbf{s}_i - h > -1) \\ 0 & (otherwise) \end{cases} \tag{9}$$

The soft-margin SVM is, then, defined as an optimization problem to minimize a cost function defined by,

$$L(\mathbf{w}, \xi) = \frac{1}{2}\|\mathbf{w}\|^2 + C \sum_{i=1}^{N} q_i \xi_i \tag{10}$$

subject to

$$\xi_i \geq 0, \; t_i \cdot (\mathbf{w}^T \mathbf{s}_i - h) \geq 1 - \xi_i, \; (i = 1, \ldots, N), \tag{11}$$

where $\xi = \{\xi_i | i = 1, \cdots, N\}$. C stands for a *cost* parameter for ξ. q_i is a weight for the i-th sample defined by,

$$q_i = \begin{cases} 1 & \mathbf{s}_i \in C_l \\ |x \in C_l| / |x \in C_s| & \mathbf{s}_i \in C_s \end{cases} \tag{12}$$

where C_s and C_l indicate the smaller and the larger class, respectively.

Mentioned above, there are three types of identifiers such like Table 2.

Table 2: The number of data and class weight.

Identifier	*spin*	*flat*	*slice*
positive sample	46	16	30
negative sample	46	76	62
q_i	1	5	2

Solving this problem with an optimal solution α, the classification function can be redefined as

$$\begin{aligned} y &= \text{sign}\ (\mathbf{w}^T \mathbf{s} - h) \\ &= \text{sign}\ (\sum_{i \in \mathbf{S}} \alpha_i t_i \mathbf{s}_i^T \mathbf{s} - h). \end{aligned} \quad (13)$$

where S stands for the indices of the support vectors. The samples are grouped with α_i; a sample $\mathbf{s}_i$ is classified correctly when $\alpha_i = 0$, when $0 < \alpha_i < C$ the sample $\mathbf{s}_i$ is also classified correctly and it locates on the hyperplane H1 (or H2) as a support-vector, if $\alpha_i = C$ the sample $\mathbf{s}_i$ becomes a support-vector but it locates between H1 and H2 with $\xi \neq 0$.

The recorded signal data was fed into the support vector machine (SVM). The number of data examples was 92. Therefore, a method called the Leave One Out Cross-Validation (LOOCV), which splits up the sample into two categories: validation data, made up of one data from the sample, and training data, made up of the rest of the data in the sample, was used to examine the data. The sample was given a class weight, and the classification was carried out accordingly. Using LOOCV is advantageous as it prevents overfitting for few data, as observations are made on *N-1* samples.

The present method identifies one rotation direction and others, such like *spin* and not *spin* (*flat and slice*). Then, using the hyperparameter optimization function in MATLAB, the parameter of the soft margin in which the accuracy was at maximum, was set.

5 EVALUATION

The proposed method is validated with the constructed ball hitting sound database and sound clips selected from YouTube videos.

5.1 Identification with Recorded Ball Hitting Sound Database

Each recorded sound clip was fed into the support vector machine (SVM) as an input. The data set was as small as 92, and the evaluation was performed by LOOCV explained in the previous section in order to prevent over-fitting and to maintain open test.

For each rotation, the hyper parameters such as a soft margin were optimized using MATLAB to maximize the accuracy.

Figures 6a-6c illustrate the answer rates for identification of *spin*, *flat*, and *slice* from the sound clip using the constructed ball hitting sound database. The horizontal axis of each figure shows the number of feature dimensions up to 91 in the descending order of eigenvalues. It is clear that, the accuracy is over 70% for all rotation directions. It is remarkable that the accuracy with 91 dimensions is almost identical to that with 20 dimensions. In other words, the analysis can be effectively and accurately performed with 20 dimensions.

Table 3: Confusion matrix for identification of each ball rotation direction. All 92 samples were identified with 91 dimensional features.

(a) Confusion matrix for identification of *spin* and others.

	spin (correct)	others (correct)
spin (prediction)	35	10
others (prediction)	11	36

(b) Confusion matrix for identification of *flat* and others.

	flat (correct)	others (correct)
flat (prediction)	11	14
others (prediction)	5	62

(c) Confusion matrix for identification of *slice* and others.

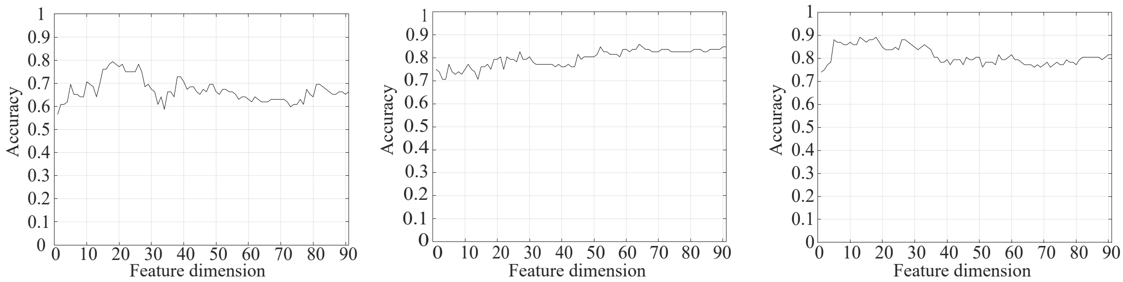
	slice (correct)	others (correct)
slice (prediction)	27	11
others (prediction)	3	51

Tables 3 show confusion matrices of 2-class identification tasks with 91 feature dimensions. Each table illustrates true-positive, true-negative, false-positive, and false-negative scores of the identification task. As mentioned above, accuracy of more than 70% was obtained for all three rotations , but the precision has different characteristics. The precision of identifying *flat* is remarkably low like 44%, while the precision of identifying *spin* and *slice* exceeds 70%. This is also linked to the low F value for *flat*.

5.2 Analysis of YouTube Clips

To apply the proposed method to YouTube clips, a video including ball hitting sounds by a professional tennis player were selected. The selected video is of the world's fourth-ranked Roger Federer practicing at the Australian Open (hard court) in January 2020[1]. From the video, 5 *spin* samples and 5 *slice* samples were picked up. After that, 50 ms ball hitting sound clips were extracted from each video in the same man-

[1] https://youtu.be/hTn42aJIhk8



(a) Accuracy for *spin*. (b) Accuracy for *flat*. (c) Accuracy for *slice*.

Figure 6: Accuracy for each spin direcsion. The horizontal and vertical axes indicate the feature dimension and the accuracy of two class identification between one rotation direction and others, respectively. The accuracy is defined as the number of correctly identified sounds divided by the total number of sounds.

Table 4: Confusion matrix for hitting sound identification. It uses 91 feature dimensions.

(a) Identification result of *spin* and others from YouTube clips.

	spin (correct)	others (correct)
spin (prediction)	5	0
others (prediction)	0	5

(b) Identification result of *slice* and others from YouTube clips.

	slice (correct)	others (correct)
slice (prediction)	5	0
others (prediction)	0	5

ner as it was done when constructing the database. Since the sampling rate of YouTube video sound is 44100 Hz, it was resampled at 16 kHz using the Audacity. Since overtaking from experiment result, the number of feature dimensions was set to 91.

Tables 4a and 4b show the results of identification for *spin* and *slice*, respectively. All 10 clips from YouTube were 100% identified.

5.3 Discussion

This section discusses the results obtained from the experiments using our own recorded sound and YouTube clips. Not only our own recorded data but YouTube data were successfully identified with high accuracy. One problem is that identification performance for *flat* shots was poor. This problem is considered to be caused by a small number of *flat* data. The training data set consists of 46 *spin*, 16 *flat* and 30 *slice* shots. The lack of *flat* data and data unbalancing between three kinds of shots resulted in poor precision for *flat* data identification. Generally speaking, when focusing on an individual tennis player, it is natural that *spin* and *slice* are easy to be distinguished from each other, but *flat* is difficult to be detected. This will be supported by the fact that *spin* and *slice* are in the opposite direction of rotation, and *flat* has less rotation, that is, between *spin* and *slice*.

When the first principal component is analyzed, we found that many of determining features are related to a frequency range 250-1100 Hz. This shows that relatively a low frequency range is needed for good identification although a hitting sound is impulsive with wide spectrum.

6 CONCLUSION

This paper describes identification of the rotation direction of tennis ball from hitting sound. We considered three class identification, that is, *spin*, *flat*, and *slice*, and proposed a rotation direction identification method based on support vector machine and principal component analysis. We also constructed a hitting sound database consisting of 92 hitting sounds with labels. Using the constructed database, the accuracy of spin identification was over 70% for each of three classes, although the precision of *flat* was only about 44% due to unbalanced data and the small number of *flat* data. The proposed method was also applied to 10 clips selected from YouTube, and in all cases the shots were successfully identified. Our detail analysis showed that the first principal component depends heavily on 250-1100 Hz features, which is interesting because hitting sound is impulsive with a lot of high frequencies in the spectrum.

7 FUTURE WORK

For YouTube, all 10 clips were successfully identified, which shows that the models trained with SVM worked properly, although the number of YouTube clips is still small. Since the number of data is limited, we need to confirm the generality using a large amount of data. Also, the robustness of the identification should be verified, because other noise sources will be mixed into the input sound, and the distance between a microphone and a sound source can not be well controlled in practice, and the deference of experiment place and weather. Future work also includes an extension of the proposed method to estimate more information such as the number of revolutions and the ball speed.

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