Strikes-Thrusts Activity Recognition Using Wrist Sensor Towards Pervasive Kendo Support System

Masashi Takata, Yugo Nakamura, Yohei Torigoe, Manato Fujimoto, Yutaka Arakawa, Keiichi Yasumoto
Graduate School of Information Science, Nara Institute of Science and Technology,
Ikoma, Nara 630-0192, Japan
Email:(masashi.takata.td7, nakamura.yugo.ns0, torigoe.yohei.tp9, manato, ara, yasumoto)@is.naist.jp

***Abstract*—In this paper, we focus on Kendo, which is a traditional sport in Japan, and propose a strikes-thrusts activity recognition method using a wrist sensor towards a pervasive Kendo support system. We collected the inertial sensor data set from 6 subjects. We attached 3 inertial sensor units (IMUs) on the subjects body, and 2 IMUs on the Shinai (bamboo sword used for Kendo). On the body, IMUs were placed on the Right Wrist, Waist and Right Ankle. On the Shinai, they were placed on the Tsuba and Saki-Gawa. We first classified strikes-thrusts activities consisting of 4 general types, Men, Tsuki, Do, and Kote, followed by further classification into 8 detailed types. We achieved 90.0% of F-measure in the case of 4-type classification and 82.6% of F-measure in the case of 8-type classification when learning and testing the same subjects data for only Right Wrist. Further, when adding data of sensors attached to the Waist and Right Ankle, we achieved 97.5% of F-measure for 4-type classification and 91.4% of F-measure for 8-type classification. As a result of leave-one-person-out cross-validation from 6 subjects to confirm generalized performance, in the case of 4-type classification, we achieved 77.5% of F-measure by using only 2 IMUs (Right Wrist and Shinai Tsuba).**

***Keywords*—Wrist sensor, Activity recognition, Machine learning, Wearable computing, Sensor position, Sports support, Kendo**

I. Introduction

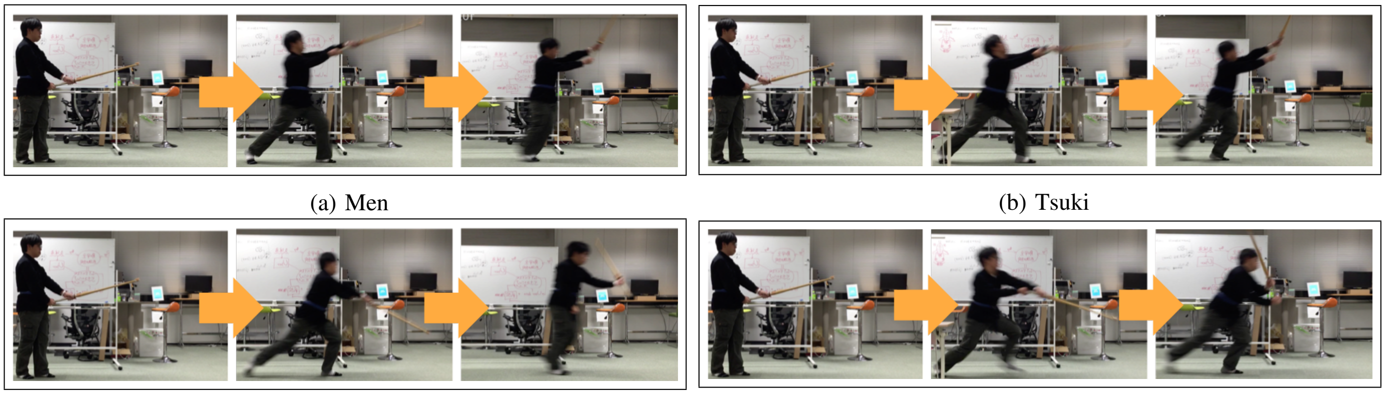
In recent years, the utilization of information technology in sports fields is rapidly increasing. It is expected that detailed analysis and feedback provided by information technology will lead to performance improvement and enhancement of the training process [1]. In basketball and climbing, there were studies that analyzed the activity using an inertial sensor unit (IMU) attached on the wrist [2], [3].

We have also been studying motion recognition and support in body-weight training [4], which is a basic sports activity, by using IMUs. We clarified that attaching IMUs to the wrist and waist can recognize training type with high accuracy. In this way, utilization of IMUs has great potential in the analysis of sports performance [5]. In the near future, IMU-based sports performance analysis is expected to be widely adopted to various sports fields. Since IMUs have already been widely used in smartphones and smartwatches, even amateur sports can easily benefit from IMU-based sports performance analysis. However, in the field of Kendo, which is a traditional sport in Japan, only discussions on data obtained by a pressure sensor pasted to the grip of the Shinai differing among players have been done [6].

In this paper, we focus on Kendo and propose a novel activity recognition approach by using a wrist-worn sensor. Kendo is a kind of combat sports that players who wear protective gear strike and thrust at each other in predetermined places by the Shinai. Strikes-thrusts activities consist of 4 types: Men, Tsuki, Do, and Kote. In Kendo, Ki-ken-tai, which is harmony between spirit, Shinai handling, and overall body movement during striking, is very important to gain a point. Therefore, it is necessary to master each strikes-thrusts activity perfectly in order to improve skill in Kendo.

One of the best ways to improve Kendo skills is to practice swinging action. Swing practice can help to understand the body movement required for an accurate strikes-thrusts activity. At this time, it is better not to do it by oneself, but to get advice based on objective information from a coach and other players. However, in actuality, it is difficult for each student to get sufficient advice for each activity because the coach instructs multiple students. This problem causes deterioration in practice efficiency and motivation. Furthermore, practicing with the wrong forms and actions may become a cause of injuries.

The objective of this study is to realize a novel support system which allows players to perform effective Kendo practice that improves practice efficiency and performance alone, by using wearable IMU devices. As a first step, we propose a strikes-thrusts swing motion recognition method. Specifically, we collected the inertial sensor data from 6 subjects. In our experiment, IMUs are attached on the body (Right Wrist, Waist, Right Ankle) and Shinai (Tsuba and Saki-Gawa). Moreover, we created a classifier for strikes-thrusts activity from the collected data set (1,440s) from 6 subjects. We first classified strikes-thrusts activities consisting of 4 general types, Men, Tsuki, Do, and Kote, followed by further classification into 8 detailed types. We achieved 90.0% of F-measure in the case of 4-type classification and 82.6% of F-measure in the case of 8-type classification when learning and testing the same subjects data of only Right Wrist. Further, when adding data of sensors attached to Waist and Right Ankle, we achieved 97.5% of F-measure for 4-type classification and 91.4% of F-measure for 8-type classification. As a result of leave-one-person-out cross-validation from 6 subjects to confirm generalized performance, in the case of 4-type classification, we achieved 77.5% of F-measure by using only 2 IMUs (Right Wrist and Shinai Tsuba).



(a) Men

(b) Tsuki

(c) Do

(d) Kote

Fig. 1: Strikes-thrusts activities

II. Related Work

Sports biomechanics using information technology provides the best tool for sports activity analysis and a monitoring system [1]. Several methods for sports biomechanics have been proposed and those can be classified into two approaches: *A*) a camera-based method that analyzes images of sports activity taken by the camera; *B*) a sensor-based method that analyzes sensor data obtained by an IMU attached to a body part.

A. Camera-Based Method

Since the camera-based method can measure without attaching any devices on the body, it is one of the best methods in sport analysis. There is an optical motion capture system [7] which is used for measurement of high-speed activity of sports and DLT (Direct Linear Transformation) method [8] using a digital video camera. These methods are frequently used for more accurate measurement. However, as these methods are large-scale and expensive, the measurement range is limited, and detailed points such as blind spots cannot be measured using these methods.

B. Sensor-Based Method

There are many studies that analyze activity during sports by using IMUs and provide effective feedback to the players so that they can practice efficiently. Blank et al. [9] attached inertial sensors to table tennis rackets and recognized 8 different basic stroke types using collected data from 10 amateur and professional players. Kosmalla et al. [3] proposed a system that automatically recognizes the route of climbing by using IMU devices placed on both wrists. James et al. [10] analyzed Men, which is the most basic strikes-thrusts activity, by attaching an accelerometer at the Saki-Gawa end of the Shinai. As a result, they reported that the accelerometer can quantitatively evaluate that difference in swing characteristics between beginners and professionals. However, they did not measure other strikes-thrusts activities and did not recognize that activity by machine learning.

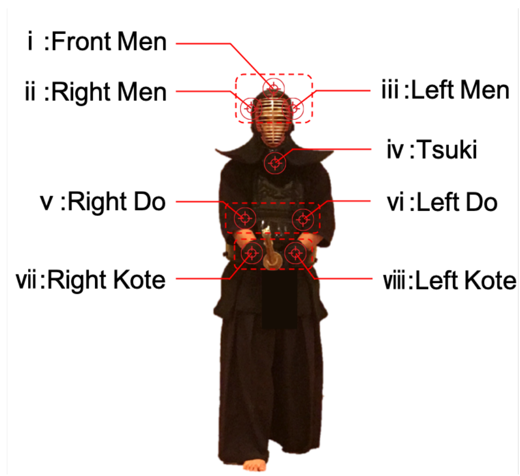


Fig. 2: The names of striking positions (classification labels)

III. Strikes-Thrusts Activity Recognition

In this section, we propose an automatic strikes-thrusts activity recognition by using IMUs with an aim to improve practice efficiency and performance.

A. Overview

The final goal of this research is to realize a Kendo monitoring system that can recognize the strikes-thrusts activity of the swing by using IMUs and give feedback for improvement. As a first step towards this goal, this paper focuses on the recognition of strikes-thrusts activity during the swing.

B. Target Activity

Fig. 1 shows 4 basic strikes-thrusts activities, that is, the target activities in this research. The names of the basic strikes-thrusts activities are Men, Tsuki, Do(dō), and Kote, and the explanations of these are as follows.

- Men

  Men is the most basic strike activity, where the player strikes the opponents head with the Shinai.

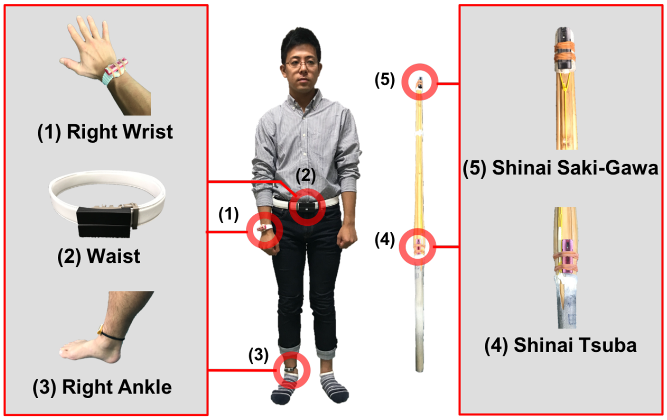
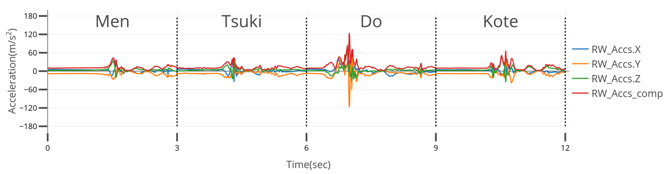
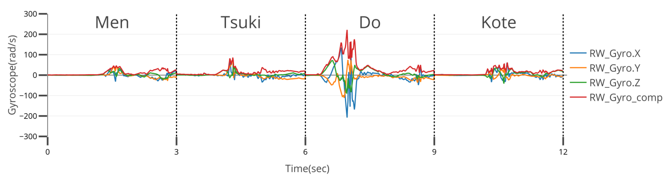


Fig. 3: The positions of IMUs attached on the body and Shinai



(a) Acceleration



(b) Gyroscope

Fig. 4: An example waveform of Kendo activity

Further, there is a strike to the right or left side of the opponents head.

- Tsuki

  Tsuki means to thrust to the opponents throat with the pointy end of the Shinai.

- Do

  Do is the strike activity to hit the opponents upper body with the Shinai. In principle, striking the right side of the body is mainstream in Kendo, but players can also strike the left side of the body.

- Kote

  Kote is to strike the opponents the wrist with the Shinai.

We define the names of striking positions as shown in Fig 2. These are also used as labels of classification in the latter section.

C. Sensors Type and Position

The IMUs used in this study are the MPU-9250, a popular IMU by InvenSense, embedded on a SenStick [11], which is a tiny multi-sensing board developed for recognizing strikes-thrusts activity, that has 8 kinds of typical sensors (accelerometer, gyroscope, magnetic, temperature, humidity, pressure, light, UV). Also, it can record all the sensing data to on-board memory at up to 100 Hz. Furthermore, it can send data to a smart phone or PC via low-energy Bluetooth. We set the sampling rate of IMUs to 100 Hz to accurately measure the activities because strikes-thrusts activities are very fast. The position of the IMU is an important issue in this research because it has to avoid affecting the play and the position will affect the recognition accuracy. In this study, we selected five positions as shown in Fig. 3. Three IMUs are attached on the body ((1) Right Wrist, (2) Waist and (3) Right Ankle), and two IMUs are attached on the Shinai ((4) Shinai Tsuba and (5) Shinai Saki-Gawa). Fig. 4 shows an example of acceleration and a gyro waveform measured by the SenStick attached to the Right Wrist.

D. Feature Engineering

We firstly calculated the composite data of each sensor by using the following equation (1).

$$composite = \sqrt{(x^2 + y^2 + z^2)} \tag{1}$$

The window size used in this study is 3 seconds, although it was empirically decided by observing the collected waveform. We consider that 3 seconds of data includes enough data to represent the characteristics of each strikes-thrusts activity. After dividing the data, we calculated the various features shown in TABLE I. For the time domain features, we extracted thirteen kinds of features: Maximum, Minimum, Average, Standard Deviation, Sum, Range (Maximum - Minimum), Variance, Median Absolute Deviation, Interquartile Range, Kurtosis, Root Mean Square, and Correlation. For the frequency domain features, we extracted 6 kinds of features: Highest Magnitude, Total Energy, Highest Magnitude Located, Entropy, Kurtosis, and Skewness. The reason why we used

TABLE I: List of Features

Time Domain Features
Maximum, Minimum, Average, Standard Deviation, Sum, Range (Maximum-Minimum), Variance, Median Absolute Deviation, Interquartile Range, Kurtosis, Root Mean Square, Correlation
Frequency Domain Features
Highest Magnitude, Total Energy, Highest Magnitude Located, Entropy, Kurtosis, Skewness

TABLE II: Subjects Data

Subjects	Age	Weight(kg)	Height(cm)	Gender	Career(year)
A	22	45.0	157	Woman	0
B	23	55.4	160	Man	0
C	23	70.0	171	Man	0
D	23	82.0	174	Man	2
E	23	62.0	177	Man	1
F	23	82.0	175	Man	0

these features is that previous work on context-aware systems using inertial data have validated the effectiveness of these features [12], [13].

IV. Experiment

A. Experimental Setup for Data Collection

To evaluate our proposed algorithm, we collected the actual activity data from 6 subjects. Subjects received guidance from an experienced person before performing and performed 10 sets of strikes-thrusts activities after setting the posture of guard. Finally, we recorded a data set of 1,440 seconds (480 sets) from the subjects shown in TABLE II. Besides tracking the subject sensor data, all strikes-thrusts activities were also captured on video and were segmented based on the video manually.

B. Strikes-Thrusts Activity Recognition

We use machine learning for recognizing strikes-thrusts activities. To compare the accuracy, we adopted four kinds of machine learning algorithms: Random Forest (RF), Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Neural Network (NN). Four-type classification labels ([i, ii, iii], [iv], [v, vi], [vii, viii]) and 8-type classification labels ([i], [ii], [iii], [iv], [v], [vi], [vii], [viii]) are manually assigned before adopting machine learning. Scikit-learn [14], a machine learning library, was used for building a learning model.

In the experiments, we considered two cases: person dependent (PD) and person independent (PI). In the PD case, 9 sets of data recorded with a particular subject were employed for training, and the other 1 set of data was used for the test. We evaluated each set to be test data once by cross-validation. In the PI case, we performed leave-one-person-out cross-validation, where in each fold, 5 persons were used for training and the remaining one was used for the tests.

V. Results & Discussion

We discuss recognition results through *A*) comparison of 4 machine learning algorithms, *B*) comparison of each combination of IMU positions, *C*) evaluation of versatility by leave-one-person-out cross-validation, and *D*) feasibility of our proposed system.

Fig. 5 shows the average of six subjects with the classification accuracy results (F-measure) of strikes-thrusts activity based on individual-only data using four different machine learning algorithms (RF, SVM, KNN, NN). The horizontal axis shows combinations of IMU positions. Machine learning algorithms are differentiated by color.

A. Comparison of 4 Machine Learning Algorithms

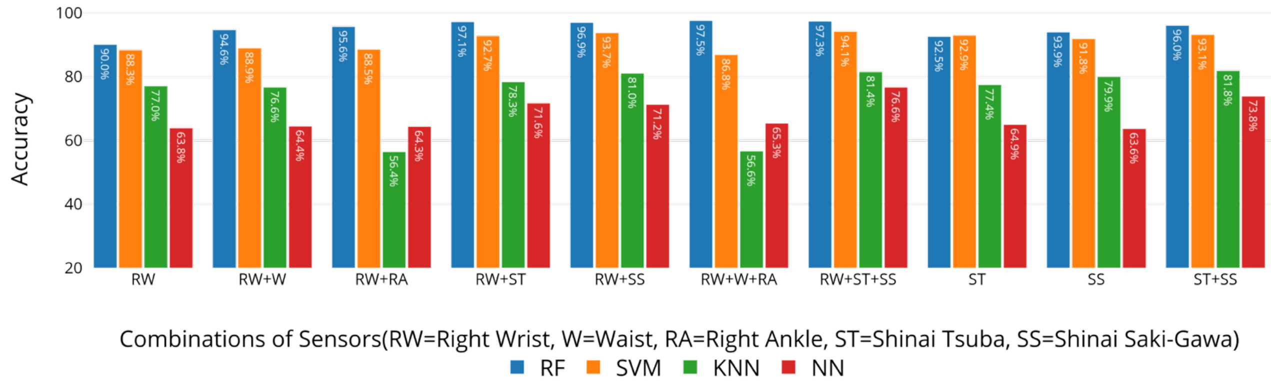
In the PD case, we compared the performance of the 4 machine learning algorithms (RF, SVM, KNN, NN). Fig. 5 (a) shows that Random Forest (RF) achieves the best accuracy, 94.0% (F-measure). In contrast, the worst accuracy was 67.9% (F-measure) by Neural Network (NN). We observed the same tendency in the case of 8-type classification. Therefore, we confirmed that Random Forest (RF) is effective as a machine learning algorithm to recognize strikes-thrusts activity accurately.

B. Comparison of Each Combination of IMU Positions

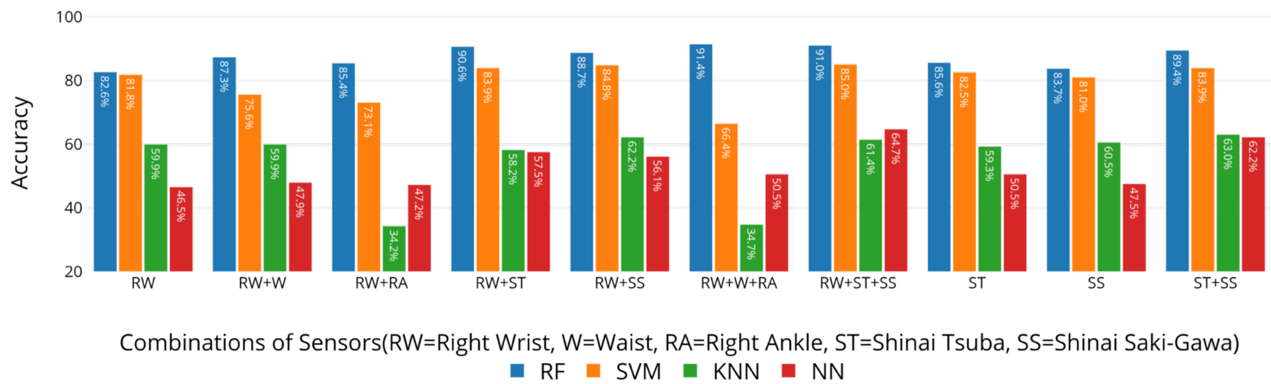
Since our final goal is to pervasively support Kendo players with just the wrist-worn sensor, it is necessary to recognize a strikes-thrusts activity when only sensors are attached to the body with the same accuracy as when sensors are attached to the Shinai. We first compared the recognition accuracy of the sensor attached to the Shinai and the wrist-worn IMU. As a result, in the case of an IMU attached on the Shinai only, we achieved Shinai Tsuba (ST): 92.5% (F-measure) and Shinai Saki-Gawa (SS): 93.9% (F-measure) with 4-type classification and Shinai Tsuba (ST): 85.6% (F-measure) and Shinai Saki-Gawa (SS): 83.7% (F-measure) with 8-type classification. Next, for the case when an IMU is attached on the Right Wrist (RW) only, our proposed algorithm achieved 90.0% (F-measure) in the case of 4-type classification and 82.6% (F-measure) in the case of 8-type classification. Therefore, we found that the wrist-worn sensor can recognize strikes-thrusts activity with almost the same accuracy as the sensor attached to the Shinai. We investigated the recognition accuracy of the strikes-thrusts activity for the combination of the wrist sensor and other body sensors. As a result, for the case when an IMU is attached to Right Wrist and Waist (W), our proposed algorithm achieved 94.6% (F-measure) in the case of 4-type classification and 88.9% (F-measure) in the case of 8-type classification. And, as a result, in the case when IMUs are attached on the Right Wrist and Right Ankle (RA), the proposed algorithm achieved 95.6% (F-measure) in the case of 4-type classification and 88.5% (F-measure) in the case of 8-type classification. Further, when IMUs are attached on the Right Wrist, Waist and Right Ankle, the proposed algorithm achieved 97.5% (F-measure) in the case of 4-type classification and 91.4% (F-measure) in the case of 8-type classification. Therefore, we clarified that if other sensors are combined with the wrist sensor, the accuracy will be further improved.

C. Results of Leave-One-Person-Out Cross-Validation

We evaluated the recognition accuracy of strikes-thrusts activity by leave-one-person-out cross-validation to confirm generalized performance. We used Random Forest (RF) which has the best performance in Section V-A as a machine learning algorithm. Also, we optimized the parameters of Random Forest (RF) by grid search. TABLE III and IV show the results of leave-one-person-out cross-validation. In the case of 4-type classification, the combination of the Right Wrist (RW) and Shinai Tsuba achieved the best accuracy, 77.5% (F-measure). Fig. 6 (a) shows a confusion matrix of the combination of Right Wrist and Shinai Tsuba (ST). This result was the same as the combination result as in Section V-B. In the case of 8-type classification, Shinai Tsuba achieved the best accuracy, 62.2% (F-measure). Fig. 6 (b) shows a confusion matrix of the Shinai Tsuba. On the other hand, the accuracy with sensors attached only to the body is relatively low. We consider that the reason for low accuracy is individual differences caused by



(a) 4 types classification



(b) 8 types classification

Fig. 5: Strikes-thrusts activity recognition result by F-measure for each SenStick position and machine learning algorithm

TABLE III: Four-type classification results by F-measure by leave-one-person-out cross-validation

Label	RW	RW+W	RW+RA	RW+ST	RW+SS	RW+W+RA	RW+ST+SS	ST	SS	ST+SS
1,2,3	68.6%	62.0%	53.9%	77.6%	76.6%	51.5%	74.6%	68.0%	59.7%	67.0%
4	12.1%	0.00%	25.5%	85.5%	74.8%	29.6%	68.4%	62.7%	63.9%	64.5%
5,6	85.8%	83.8%	85.1%	89.6%	90.8%	81.5%	96.2%	85.2%	81.8%	81.1%
7,8	52.4%	41.9%	37.0%	61.2%	53.3%	36.1%	63.7%	54.8%	42.6%	56.9%
avg.	**60.8%**	**54.6%**	**53.8%**	**77.5%**	**74.0%**	**52.4%**	**76.4%**	**68.3%**	**61.4%**	**67.0%**

fact that subjects included inexperienced persons. Therefore, we confirmed that if we performed recognition based only on personal data, we can recognize the strikes-thrusts activity with high accuracy as in Section V-B. However, due to individual differences in activity, the accuracy of leave-one-person-out cross-validation decreases.

D. Feasibility of our proposed system

Through the evaluation, we confirmed that the sensor combination of RW+ST achieved good accuracy for both 8-type and 4-type classification. Since smart watches such as the Apple Watch have already become popular, the sensor on the wrist is feasible. On the other hand, there are no Shinai in which sensors are embedded in the current market. However, in different sports such as a tennis, some sensor-embedded rackets (*Babolat Play*[1], *Smart Tennis Sensor*[2]) have already been sold in the commercial market. Therefore, there is a possibility that a sensor-embedded Shinai will be released in the future. If so, our proposed system will work well and we can expect that data can be collected from various users.

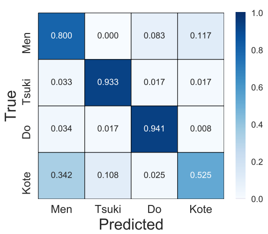
VI. Conclusion

In this paper, we focused on Kendo, which is a traditional sport in Japan, and proposed a strikes-thrusts activity recognition method using a wrist-worn sensor towards a pervasive

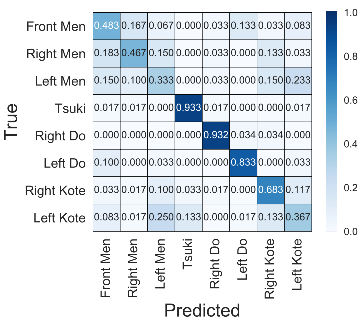
[1]Babolat Play : http://en.babolatplay.com/
[2]Smart Tennis Sensor : https://www.sony.com.au/microsite/tennis/

TABLE IV: Eight-type classification results by F-measure by leave-one-person-out cross-validation

Label	RW	RW+W	RW+RA	RW+ST	RW+SS	RW+W+RA	RW+ST+SS	ST	SS	ST+SS
1	34.3%	24.8%	40.0%	41.4%	56.5%	34.8%	59.3%	47.2%	46.4%	44.8%
2	18.8%	17.6%	23.5%	28.9%	49.0%	19.8%	49.0%	52.3%	30.6%	44.7%
3	39.6%	25.8%	26.0%	34.0%	33.7%	17.5%	29.8%	34.5%	31.1%	29.7%
4	35.0%	28.8%	37.8%	73.1%	64.2%	20.3%	69.6%	88.9%	58.7%	60.7%
5	68.6%	75.4%	57.4%	86.2%	80.0%	50.9%	93.2%	90.2%	70.2%	83.8%
6	83.3%	85.3%	74.6%	88.4%	80.0%	82.7%	91.3%	82.6%	67.2%	68.5%
7	17.9%	22.4%	22.2%	48.2%	49.0%	15.8%	64.2%	63.1%	44.2%	57.9%
8	27.7%	23.3%	18.9%	30.9%	39.7%	20.0%	32.4%	38.9%	25.8%	25.9%
avg.	**40.6%**	**37.9%**	**37.5%**	**53.8%**	**56.5%**	**32.7%**	**61.0%**	**62.2%**	**46.8%**	**51.9%**



(a) 4 types classify (RW+ST)



(b) 8 types classify (ST)

Fig. 6: Confusion matrix of leave-one-person-out cross-validation

Kendo support system. We collected the inertial sensor data from 6 subjects who attached IMUs on their Right Wrist, Waist, Right Ankle. Also, we collected the same data from Shinai where 2 IMUs were attached on Tsuba and Saki-Gawa. We first classified strikes-thrusts activities consisting of 4 general types, Men, Tsuki, Do, and Kote, followed by further classification into 8 detailed types. We achieved 90.0% of F-measure in the case of 4-type classification and 82.6% of F-measure in the case of 8-type classification when learning and testing on the same subjects data of only Right Wrist. Further, when adding data of sensors attached to the Waist and Right Ankle, we achieved 97.5% of F-measure for 4-type classification and 91.4% of F-measure for 8-type classification. Therefore, we clarified that if other sensors are combined with the wrist sensor, the accuracy will be further improved. As a result of leave-one-person-out cross-validation from 6 subjects to confirm generalized performance, in the case of 4-type classification, we achieved 77.5% of F-measure using only 2 IMUs (Right Wrist and Shinai Tsuba). Therefore, if we perform recognition based only on personal data, we can recognize a strikes-thrusts activity with high accuracy. However, due to individual differences in activity, the accuracy of leave-one-person-out cross-validation decreases. As part of future work, we aim to collect more data obtained from experienced persons whose forms are correct and stable for improving recognition accuracy and covering a diverse demographic population.

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