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Volleyball Skill Assessment Using a Single Wearable Micro Inertial Measurement Unit at Wrist

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ABSTRACT In this study, a wearable sensing device (WSD) based on microelectromechanical systems motion sensors (an inertial measurement unit consisting of sensors with three axes of acceleration and three axes of angular rate) was built to assess the skill levels of volleyball spikers. The developed WSD is inexpensive and requires much less computational power than conventional videography analysis in monitoring motions of volleyball players during spikes. This paper presents the hardware and software design and the data processing algorithms used in the system. Six right-handed male subjects wore the WSD on their wrists and performed 120 spiking trials in a volleyball court. Skill of the volleyball spikers was accessed by classifying them into three different levels from the recorded data with support vector machine. The results demonstrate that this system is capable of assessing the difference between elite, sub-elite, and amateur volleyball players with an average accuracy of 94%. The proposed method can be extended to analyze the skill levels of players in other sports, where wrist actions are important (e.g., basketball, badminton, and baseball).

INDEX TERMS Wearable devices, inertial measurement unit, sports analysis, volleyball spiking, motion assessment.

I. INTRODUCTION

Volleyball is a popular sport with more than 900 million volleyball players worldwide, as reported by the Federation International de Volleyball (FIVB) [1]. In volleyball games, spiking is the predominant skill used by a team when attacking [2]. Despite consisting of a number of movement components, from a coach’s viewpoint, spiking is relatively easy to teach because the movements used are similar to those in other popular sports (e.g., baseball and tennis). Spiking is motivational for players in the early stage of learning [3]. Similar to shooting and dunking in basketball, spiking is a rewarding terminal contact. A successful spike is a strike at the opponents. Every player, including the defender and setter, tries to spike during every game. However, it is difficult to master and execute the spiking movements consistently. Nonetheless, learning proper spiking action efficiently has been a major concern to both players and coaches.

During each spike, the spiker generates the momentum imparted to the ball. A series of factors could influence the spike efficiencies [4]:

- the linear velocity of the spiker in the direction of the spike;
- the spiker’s torso rotation, arm swing and wrist snap;
- the downward velocity of the spiker, that is, the drop velocity of the spiker before contacting the ball; and
- the mass and rigidity of the spiker’s hand.

In addition to these biomechanical factors, a reasonable spiking action and posture can reduce injury and improve performance [5]. These factors could be translated two key principles in execution [6]:

- The line of force for a right-handed spiker moves from the contact point between the hand and ball down the arm through the center of gravity and, finally, down into the athlete’s left leg.
A spiker who hits the ball is supposed to use the “top-spin” technique, which takes advantage of the Magnus effect.

To improve their spiking skills for better team performance, players have been following these biomechanical principles. Conventional methods used in current sports training and monitoring for athletes is videography. Videography is also a primary method that sports scientists and professional coaches use to study and monitor the biomechanics of various actions in sports, such as badminton, golf, football, and cricket [7]. However, there are a number of limitations in the use of videography for these purposes. For example, videography is unable to provide kinematical analysis to athletes in real-time [8]. Another limitation of video-based systems typically is the environmental restriction [9]. For instance, the amount of light, blind spots, and movements of multiple players can easily distort the results captured by the camera. In addition, because images acquired through high-speed cameras require significant amounts of storage, the computation load is high.

Because of the aforementioned limitations, an alternative solution is to use micro inertial sensors [10], [11]. The development of microelectromechanical systems (MEMS) technologies have provided low-cost and effective solutions with micro inertial sensors for sports monitoring and action recognition [12]. Although there were attempts in collecting athletes’ kinematics data with MEMS sensors, relatively limited analyses were previously conducted on how to utilize these data for training [13]. An inertial information database was constructed for professional horseback riders that used 16 motion sensors and then the respective motion features were extracted from the sensor data, i.e., elbow angle, knee angle, backbone angle, hip position, and knee-elbow distance [14]. Another good example is that Ermes et al. [15] developed a system using MEMS sensors to collect sports activities data including running, cycling, and playing football. Recent research activities also explore the use of MEMS sensors to count typical routines in sports. For instance, the frequency of jumps in volleyball games has been investigated using a tri-axial accelerometer [16].

Golf analysis system using MEMS sensors has also been commercialized for training. In such a golf swing training system, five accelerometers and five gyroscopes are used to measure acceleration and angular displacement, which provides feedback on the quality of the swing movement [17]. Yet, for wearable applications, there is a lack of investigation on reducing the number of sensors required to realize the same functionalities. More recent studies demonstrated the potential of identifying novice and experienced piano players from synergies [18]. However, to date, no motion sensor system has been built for the purpose of monitoring and coaching of volleyball spiking motions.

Amateurs often have trouble in learning volleyball-spiking mechanisms. In this work, we propose a novel intelligent sensing system based on inertial sensors to assess volleyball spiking skills. The system developed is capable of differentiating the skill levels between elite volleyball athletes and amateur players. At the same time, the system provides a feedback for the quality of the players’ spiking motion. First, we designed and developed a wearable device with an overall size of 18mm × 16mm × 2mm to collect inertial data. Second, we developed a software that fused video data and inertial data to allow verification of the collected motion data through visual validation. Using these developed technologies, we have shown that machine learning algorithms can be used to discriminate the skill levels between elite volleyball athletes and amateur players -- reaching a high prediction accuracy of 94%. It should be noted that this framework can also be extended to analyze skill levels of players in other sports activities in which wrist actions are crucial, including basketball, badminton, baseball, etc.

II. SYSTEM SETUP

This section describes a comprehensive and smart coaching device for users to monitor volleyball spiking activity. As shown in Fig. 1, the system consists of sensor nodes, a high-speed camera and a computer for data collection, motion review, and data analysis respectively.

A. HARDWARE SYSTEM

Existing commercial products, such as STT-IBS inertial sensors, Shammer3 from Shammer Sensing, and Opal sensors from APDM Wearable Technologies, do not fit the size requirement and are limited in measurement range. For example, the dimension of Shimmer3 and Opal are 51mm × 34mm × 14mm and 43.7mm × 39.7mm × 13.7mm, respectively, and hence, both relatively large and inconvenient to be worn by players throughout a volleyball game. Fig. 2 shows our micro inertial measurement unit (IMU) design with four major components: a MEMS motion sensor, a microprocessor, a battery, and a microSD card. We have used the MPU9250 (TDK InvenSense, USA) to build a customized sensor system. ATmega328 (Microchip, USA) was adopted.
as the micro controller unit (MCU), which communicates with the motion sensor and stores the recordings to the microSD card. This MCU can be programmed using the Arduino development kit, an open-source electronics platform. The size of the entire IMU can be reduced into a 18 mm \times 16 mm \times 2 mm package.

Concerning the range of recorded data, commercial wearable products are usually designed for general purposes, such as steps counting and indoor activities recognition, but not for high-impact sports like volleyball. They have only two ranges including 2g and 8g. As our device aims to collect spiking action data from athletes, a sensor chip with a suitable measurement range is necessary. Therefore, we selected the MPU9250 with much higher maximum range (16g) and smaller size (3mm \times 3mm \times 1mm). MPU9250 is a nine-axis MEMS motion sensor that provides both orientation (through a built-in gyroscope) and acceleration (through a built-in accelerometer) readings in x-y-z dimensions. The maximum range of the accelerometer is 16g, which is fast enough to capture the volleyball spike activity.

As the proof-of-concept if IMU is useful in volleyball skill assessment, the proposed system has the high-speed camera to validate the inertial information received from the sensors and to perform segmentation manually, as described in Section 4.2. We chose the BASLER acA2000-165 \mu m camera as it meets the frame rate, resolution and cost requirements. This camera can freeze fast-moving objects in indoor sports centers and provides high definition. Table 1 shows the specifications of the acA2000-165 \mu m camera.

### III. METHODS OF EXPERIMENT

Our experiments were conducted at Shek Kip Mei Stadium (in the vicinity of CityU in Kowloon Tong, Hong Kong). Ten right-handed male volleyball players, including three amateurs, three sub-elites, and four elite volleyball players participated in the study. Their demographies are shown in Table 2. The experimental procedures were reviewed and approved by the Ethics Committee of the City University of Hong Kong, and all the participants provided written informed consent before participation. Elite players had represented their region with more than 10 non-local competitions. Sub-elite players had played in local competitions but have no experience playing in non-local competitions. Amateurs were beginners in playing volleyball.

### TABLE 1. Specifications of the acA2000-165 \mu m camera [19].

<table>
<thead>
<tr>
<th>Product</th>
<th>acA2000-165 \mu m</th>
</tr>
</thead>
<tbody>
<tr>
<td>Resolution</td>
<td>2,048 px \times 1,088 px</td>
</tr>
<tr>
<td>Frame rate</td>
<td>165 fps</td>
</tr>
<tr>
<td>Mono/Color</td>
<td>\pm 4,800 \mu T</td>
</tr>
<tr>
<td>Interface</td>
<td>USB 3.0</td>
</tr>
<tr>
<td>Exposure control</td>
<td>Programmable via camera API</td>
</tr>
<tr>
<td>Pixel depth</td>
<td>10,12 bits</td>
</tr>
</tbody>
</table>

### TABLE 2. Information about the subjects.

<table>
<thead>
<tr>
<th>Subject</th>
<th>Age</th>
<th>Height</th>
<th>Body Mass</th>
</tr>
</thead>
<tbody>
<tr>
<td>Elite A</td>
<td>22</td>
<td>193 cm</td>
<td>85 kg</td>
</tr>
<tr>
<td>Elite B</td>
<td>25</td>
<td>193 cm</td>
<td>94 kg</td>
</tr>
<tr>
<td>Elite C</td>
<td>22</td>
<td>193 cm</td>
<td>86 kg</td>
</tr>
<tr>
<td>Elite D</td>
<td>21</td>
<td>188 cm</td>
<td>75 kg</td>
</tr>
<tr>
<td>Sub-elite A</td>
<td>29</td>
<td>188 cm</td>
<td>86 kg</td>
</tr>
<tr>
<td>Sub-elite B</td>
<td>26</td>
<td>186 cm</td>
<td>84 kg</td>
</tr>
<tr>
<td>Sub-elite C</td>
<td>25</td>
<td>186 cm</td>
<td>82 kg</td>
</tr>
<tr>
<td>Amateur A</td>
<td>25</td>
<td>183 cm</td>
<td>70 kg</td>
</tr>
<tr>
<td>Amateur B</td>
<td>26</td>
<td>179 cm</td>
<td>71 kg</td>
</tr>
<tr>
<td>Amateur C</td>
<td>28</td>
<td>180 cm</td>
<td>74 kg</td>
</tr>
</tbody>
</table>

Each subject wore our customized sensor on their wrist while performing spikes. The sensor unit was placed on the wrist during the experiment to ensure that the major inertial information of spiking can be captured by our system without obstruction. The motion capture system shown in Fig. 4a was also created to validate the timing of sensor data.

After a 20-minute warmup supervised by a professional coach, each subject performed 10 cross-court spikes using a straight-ahead spike motion. Fig. 4 shows the route that these volleyball spikes must take during the tests. Each subject had to spike the ball toward the “x” position; otherwise, we did not count it as a successful spike.

Fig. 5 shows an experimental image taken by the high-speed camera. Two spikers are approaching the ball. Subject in Fig. 5a is an amateur, while the subject in Fig. 5b is an elite volleyball player.
Fig. 6 displays the raw data captured by the WSD. The first two rows show the angular velocity and acceleration from the amateur depicted in Fig. 5a, while the second two rows show the inertial information from 6-axes for the elite player. Fig. 7 shows the six-axis synchronized raw data from players at different levels.

IV. DATA PROCESSING

After data collection, we followed typical data analysis steps, including preprocessing, segmentation, feature extraction, dimensionality reduction and classification. In data preprocessing, data points associated with the subject failing to spike the ball inside the target area were removed. We first loaded the raw data $\dot{S}(t)_{ij}$ from each subject as shown in Algorithm 1 below, where $i$ denotes $i$th volleyball subject and $j$ represents the $j$th sensor node. Then, in Step 2 of Algorithm 1, we applied a 3-point filter moving average to reduce the effect of noise and obtain a clearer $S(t)_{ij}$ signal.
The statistical and morphology features were extracted and each dataset $X_i = (f_1 \ldots f_m)$ was merged into a large matrix $\tilde{X}$ in Steps 3–5, where $m$ represents the number of features.

In our preliminary study, 12 statistical features and 3 morphological features were extracted and used as inputs for skill level recognition and classification for proof-of-concept. These features included 1) mean and variance from the six axes; 2) the maximum acceleration value from the x-axis and the magnitude of the acceleration and angular velocity.

The statistical and morphology features were extracted and used as inputs for skill level recognition and classification for proof-of-concept. These features included 1) mean and variance from the six axes; 2) the maximum acceleration value from the x-axis and the magnitude of the acceleration and angular velocity.

Algorithm 1 Preparation of Skill Assessment

1: for all $i, j$ such that $1 < i < I, 1 < j < J$ do
2. Load the raw data signal $S(t)_{ij}$ and implement the 3-point moving average filter to obtain $\hat{S}(t)_{ij}$.
3. Extract the features of the $i$th volleyball spiker, $f_1 \ldots f_m$, from the raw data signal $S(t)_{ij}$ into a new matrix $\dot{X}_i$.
4: end for
5: Merge the matrices $\dot{x}_1, \ldots, \dot{x}_n$ into one matrix, $\dot{X}$.
6: for all $i$ such that $1 < i < I$, do
7: Using PCA to process each $\dot{X}_i$ to obtain the new features $c_1, \ldots, c_p$ from the old features $f_1, \ldots, f_m$ and compile a new data set $X_i$.
8: Merge the matrices $x_1, \ldots, x_n$ into one matrix $X$.
9: end for

Algorithm 2 Training the Skill Assessment Model

1: for all $i, k$ such that $1 < i < I, 1 < k < P$, do
2. $C_{ik} \leftarrow (C_{ik} - \min(C_{ik}))/ (\max(C_{ik}) - \min(C_{ik}))$.
3: end for
4: Merge the updated matrices $x_1, \ldots, x_n$ into one matrix $X$.
5: Calculate the skill assessment model by inputting the training data $X$.
5: while $i < / do
6: d(X^T) = \sum_{i=1}^{I} \gamma_i x_i^T + b_0$
7: end while

A. PRINCIPLE COMPONENT ANALYSIS (PCA)

Principle components were identified to alleviate the computing load and bandwidth requirements during communication with the SD card. We used PCA to preprocess the data before classification.

Fifteen features extracted from the raw spiking data can be expressed as vectors, where $f = [f_1, f_2, \ldots, f_{15}]$. These new features are linear combinations of the original features and can be expressed as $f_m = [f_{n1}, f_{n2}, \ldots, f_{nm}]$, where $m$ represents the dimension to be reduced:

$$f_m = a_{11}f_1 + a_{21}f_2 + \cdots + a_{m1}f_m$$

(1)

where $a_{ij}$ are eigenvalues of the covariance matrix. As we have only one node, Equation (1) can be simplified to

$$f_m = a_1f_1 + a_2f_2 + \cdots + a_nf_m$$

(2)

According to the calculation of principal component variance; using the eigenvalues of the covariance matrix, we find...
that 98.19% of the total variance can be explained by first three principal components. Therefore, we used these three principal components as an input to the next stage of data processing. Fig. 8 illustrates the PCA representation of both training data and test data.

**B. SUPPORT VECTOR MACHINE (SVM)**

Because we have three labels, amateur, sub-elite, and elite, we used a one-versus-one strategy in which a set of binary classifiers are constructed using corresponding data from the other two classes.

The hyperplane can be defined as follows:

$$W \cdot X + b = 0$$

and the weight vector can be expressed as

$$W = \{w_1, w_2 \ldots, w_n\}$$

where $X$ is the training set from the spiking samples, $b$ is the bias, and $n$ is the number of features extracted from the spiking signal. Thus, this problem can be converted to the following equation:

$$d(X^T) = \sum_{i=1}^{n} y_i a_i x_i x_i^T + b_0$$

where $y_i$ refers to the class label of support vector, $a_i$ and $b_0$ refer to two constants, and $X$ refers to the testing set of spiking samples whose labels are $y_i$. To investigate the influence of parameters in classification performance [20], we tested six sets of parameters as listed in Table 3.

Overall, 100 datasets were collected from 10 subjects, i.e., each performed 10 trials. We used seven subjects’ datasets (70 datasets) from each group for the training, and the remaining datasets (30 datasets) from another three different subjects from each group for testing classifier performances. During the training process, we used 5-fold cross validation to avoid the overfitting problem and found the best parameters of the SVM classifier. This was repeated 36 times to ensure that all possible combinations of testing sets with three subjects of different skill levels were covered.

We compared $C$ values ranging from 1 to 50000; Gamma values ranging 0.0001 to 0.1 and several different types of kernels. We found that the best classifier was achieved when $C = 1$, and when using the linear kernel function. Table 4 shows the average classification results when using SVM following PCA (SVM + PCA):

As shown in Table 5, the recognition precisions of amateurs, sub-elite players and elites are 100%, 83% and 100%, respectively. The results demonstrated clear distinction in performance between amateurs and elites. However, the performance of sub-elite players varies. On average, the precision of assessing the different levels of players reached 94%, indicating that our model is highly efficient.

**C. COMPARISON OF DIFFERENT CLASSIFIERS**

We have also compared k-Nearest-Neighbor (kNN) non-parametric classifier and Naïve Bayes (NB) classifier, as shown in Table 6, to determine whether SVM+PCA is the best classifier for our data. We tested different $k$ values (from 1 to 11) to find the best estimator for our data. Finally, we achieved the best model results when $k = 5$. The results...
from testing two other algorithms demonstrates that the computational efficient PCA + SVM is also sufficiently accurate.

V. DISCUSSION

Quantifying athletic performance is an area of interest in all sports categories. With the advances in MEMS sensors, communication technology and machine learning algorithms, it is now possible to use wearable inertial motion sensors to track athletes’ motions and monitor their performances. In this work, we developed a complete skill assessment system for volleyball spiking using a MEMS-based IMU for motion data collection, i.e., a WSD (wearable sensing device) with dimensions of 18mm × 16mm × 2mm. The WSD had successfully recorded the inertial information of volleyball spikers and stored the raw data in a MicroSD card, which could later be analyzed by a data processing unit. An interface software was also developed to visualize the collected IMU motion data and associate these data with the videos of the corresponding volleyball players’ actions, which makes the system useful for coaches and volleyball players to analyze players’ spiking motions. Using this system, we have also compiled a database of volleyball spiking movements from players at different levels, which can be used by sports scientists and professional coaches for further study and research. This study investigated 15 features to characterize each data segment. The performance levels represented by the skill data were estimated by SVM, kNN and NB classifiers. Comparisons of these classifiers showed that SVM achieves a high accuracy (94%) in assessing the volleyball spiking skill level, which could help coaches and athletes to keep track of condition changes during a training season. Hence, based on our experimental results, we have shown that the differentiation of skill levels of different players is possible using the WSD and appropriate data analyses algorithms. Once a player’s skill level is estimated using our system, a suitable training program could be offered to the player to improve their skill level, which will maximize the efficiency of training. Then, when the player completes the suitable training program, our system can be used again to measure the progress the player has made. A limitation of this study is that we did not transmit the inertial sensor information wirelessly for real-time data analyses, i.e., the current system can only use machine learning techniques to assess the different levels of players from the off-line analyses. However, for commercial applications, real-time analysis is very important. Therefore, we will improve our sensing and analyses system by collecting wireless data in real-time in the future. We envision that this system can be also applied to assess the skill levels of athletes in other sports where wrist actions are important, such as basketball, badminton and baseball.

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REFERENCES

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