Action sports science with sensor technology and statistical analysis methods

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Abstract. This paper describe how to apply sensor technology and statistical analysis methods to formalize action sports science. Action sports are composed of quick motions to achieve difficult tricks. Inertial sensors are suitable equipment to record quick motions. Statistical analysis methods are required to identify key factors to make successful tricks. To show how to apply these technology and methodologies for analysing action sports, three types of sports and three types of terrains are selected. These examples show us that the technology and methodologies can detect different sports and skill levels, while they can also identify key factors for successful tricks.

1. Introduction
This paper describe how to apply sensor technology and statistical methods to formalize action sports science. Sensor technology is widely accepted because of wide spread of smartphone use in our society. Basic activities, e.g. jogging and walking, are analysed as a task of human activity recognition [1]. Inertial sensors are also effective tools for sports performance evaluation [2] [3]. According to the review, there are many researches on team sports, individual sports, cyclic sports, winter sports, and outdoor sports. The last category contains skateboarding, which is analysed in only one paper, although it is one of the popular action sports and it will be one of the official competition in 2020 Tokyo Olympic games. This paper focuses on three types of action sports, i.e., skateboard, inline skate, and BMX. To show how to apply these technology and methodology for analysing action sports, three types of sports and three types of terrains are employed. These examples show us that the technology and methodologies can detect different skill levels and can identify key factors for successful tricks.

2. Development of wearable sensor system
Original wearable sensor system has been developed to record motion with precise time stamp to synchronize multiple time series data. Motion in action sport is very quick and high impact. Due to these very specific conditions, we developed our own recording device.

2.1. Hardware
The developed wearable sensor is composed of a microcomputer (Arduino), accelerometer and gyroscope (MPU6050), digital compass (HMC5883L), and GPS (MTK3339). The motion and location data is stored on a micro SD-card. The device’s sampling rate is approximately 50 Hz. The data...
contains a precise time stamp and position from the GPS on each record at each sampling time. The record also contains sensing data from the three-axis accelerometer, three-axis gyroscope, and three-axis digital compass [4].

2.2. Software
The sensor data is processed by pre-processing software. The software converts date and time into timestamp in the data. It also synchronizes and normalizes the timestamp on the data collected from multiple sensors on body and equipment. After normalization, it detects the time series of each action automatically [4].

3. Statistical analysis
Motion data with inertial sensors is multi-dimensional time series data. Auto-correlation and cross-correlation are suitable indexes to evaluate periodicity of body part’s motion and linkage between two different body parts’ motions. Clustering method is effective method to separate different sports and skill levels, respectively. Regression and discriminant analyses are suitable methods to identify key factors for successful tricks or actions. Statistical hypothesis testing is also effective method to evaluate statistical significance concerning identified key factors.

3.1. Correlation
Auto-correlation is suitable indexes to evaluate periodicity of body part’s motion [4]. Formulas (1), (2), and (3) are definitions of sample average $\mu_{i,j}$, sample covariance function $C_{i,j,k}$, and sample correlation function $R_{i,j,k}$ based on a time sequence $\{y_{i,j,1}, y_{i,j,2}, \ldots, y_{i,j,n}\}$, where $i$ is sequential run number, $j$ is sensor number, and $t$ is time period between 1 and $n$. Autocorrelations on all sensors’ axes are calculated to define the distance function between each pair of time series data based on the squared difference between them in formula (4), where $S$ is a set of sensors and $K$ is the maximum time lag for calculating distance.

$$\mu_{i,j} = \frac{1}{n} \sum_{t=1}^{n} y_{i,j,t},$$

$$C_{i,j,k} = \frac{1}{n} \sum_{j=k+1}^{n} (y_{i,j,t} - \mu_{i,j})(y_{i,j,k} - \mu_{i,k})$$

$$R_{i,j,k} = \frac{C_{i,j,k}}{\mu_{i,j} \mu_{i,k}}$$

$$\text{dist}(a, b, S, K) = \sum_{a \in S} \sum_{b \in S} \left( R_{a,k,b} - R_{a,k,a} \right)^2$$

Cross-correlation is suitable indexes to evaluate periodicity of body part’s motion and linkage between two different body parts’ motions. Especially, local cross-correlation is effective similarity index to analyze quick motion [5]. To define local cross-correlation, local average is defined by formula (5) with respect to a point of time series trajectory represented as $y_{c,i,j,p+t}$, where the parameters are run (c), body part of sensor (i), sensor axis (j), window size (w), start time of window (p), and time in window (t). The range of p is $[0, 1-w]$ where 1 is length of time series. A local variance is defined by formula (6). Local cross-variance between run c1 and c2 is defined by formula (7). Local cross-correlation coefficient is derived by formula (8), (9), and (10).

$$Y(p,w,c,i,j) = \frac{1}{w} \sum_{t=1}^{w} y_{c,i,j,p+t}$$

$$V(p,w,c,i,j) = \frac{1}{w-1} \sum_{t=1}^{w} (y_{c,i,j,p+t} - Y(p,w,c,i,j))^2$$

$$D(p,w,k,c1,c2,i,j) = \frac{1}{w-1} \sum_{t=1}^{w} (y_{c1,i,j,p+t} - Y(p,w,c1,i,j))(y_{c2,i,j,p-k+t} - Y(p-k,w,c2,i,j))$$
3.2. Clustering
To detect and separate different types of sports and skill levels, clustering is an effective method with certain similarity measurements as described in 3.1. To evaluate these distance measurements in 3.1, hierarchical clustering with dendrogram is suitable method for visual confirmation of measurement appropriateness. For example, good measurement can generate well separated sub-clusters, however, poor measurement is going to result bad sub-clusters which contain different types of sports and skill levels [4][5][6][7][8].

3.3. Multivariable analysis
To identify successful factors concerning sports skill and trick, multivariable analysis is an effective method, because multiple inertial sensors generate multiple variable time series data. We can apply regression analysis to identify relation between running speed and effective motion. We can also employ discriminant analysis to find effective motions in terms of each axis of an inertial sensor [9].

3.4. Statistical hypothesis testing
To identify difference between success and failure in terms of timing of motion, statistical hypothesis testing is an effective method, because the difference is evaluated in terms of statistical significance. We can employ t-test or Mann–Whitney U test to decide statistical significance of difference of motions between success and failure. A t-test is most commonly applied when the test statistic would follow a normal distribution. On the other hand, U-test does not require the assumption of normal distributions [10].

4. Type of sports and terrains
Skateboard, BMX, and inline skate are selected target action sports, because they were official competitions in X-games and the former two sports will be official competitions in 2020 Tokyo Olympic Games. Halfpipe, big air ramp, and flat ground are selected target terrains.

4.1. Periodic motion
Turn maneuver on halfpipe is periodical motion (figure 1). Auto correlation described in 3.1 is effective to calculate similarity between pair of runs on halfpipe. Hierarchical clustering based on the auto-correlation illustrates properly separated sub clusters in terms of type of sports, i.e. skateboard, inline skate, BMX, and level of skills, beginner, intermediate, and advanced (figure 2) [4].

3.2. Clustering

\[ C_{c1,c2,i,j,k,w,p} = \frac{D(p,w,k,c1,c2,i,j)}{s_{c1,i,j,w,p} s_{c2,i,j,w,p-k}} \quad \ldots \quad (8) \]

\[ s_{c1,i,j,w,p} = \sqrt{V(p,w,c1,i,j)} \quad \ldots \quad (9) \]

\[ s_{c2,i,j,w,p-k} = \sqrt{V(p - k,w,c2,i,j)} \quad \ldots \quad (10) \]

4.2. Aperiodic motion
Set of jumps on big air ramp is aperiodic motion (figure 3). Local cross correlation described in 3.1 is effective to calculate similarity between pair of different runs on big air ramp, because it focuses on
important motions and ignores the other unimportant motions. Hierarchical clustering based on the local cross-correlation illustrates properly separated sub clusters in terms of type of sports and level of skills (figure 4) [5] [6] [7].

![Figure 3. Big air ramp.](image3)
![Figure 4. Cluster with local cross-correlation.](image4)

4.3. Repetitive balance
Flatland BMX is repetitive balancing sport on flat ground (figure 5).

![Figure 5. Example trick - peg wheelie turbine.](image5)
![Figure 6. Cluster with local cross-correlation.](image6)

The local cross correlation and hierarchical clustering are also effective to classify ten tricks into similar subgroups, i.e. Turbine, Glide, Upside-down, Spinning, and Pump (figure 6) [8].

4.4. Repetitive drive
Moving forward with skateboard on flat ground is basic trick, i.e. Tic-Tac, while it is difficult for beginner. Tic-Tac is repetitive drive motion trick. Regression and discriminant analyses reveals that huge periodic swing motion of skateboard and counter motion of upper body are key factors to get fast speed (figure 7) [9].

![Figure 7. Swing and lean motions for Tic-Tac.](image7)
4.5. Trick sequence

Flipping skateboard is an advanced trick, which is composed of five steps (e) beginning, (d) preparation, (c) execution, (b) catch, and (a) landing (figure 8) [10].

![Figure 8. Kickflip sequence.](image)

The sequence is completed in approximately 200 milli-seconds. Hence, timing is the most important factor to make successful trick. Especially, the duration between (e) beginning and (d) preparation is the most important period to do successful execution or kicking skateboard in step (c). Hence, lifting front side of skateboard and preparing kick foot are statistically analyzed to find difference between success and failure cases with Mann–Whitney U test. According to the statistical hypothesis testing, longer lifting time of front side of skateboard leads to successful kickflip, because steep angled skateboard is easy to kick and flip it. Moreover, early preparation or counter rotation of kick foot is desirable to do successful kickflip [10].

5. Conclusion

This paper summarized examples of sensor technology and statistical analysis methods to formalize action sports science. Original wearable sensor system has been developed to analyze quick motions of action sports. To separate different sports and skill levels and to identify key factors to make successful action sports tricks, sensor data is analyzed with statistical methods, i.e. auto-correlation, cross-correlation, hierarchical clustering, regression, discriminant analyses, and statistical hypothesis testing. This paper explained five examples, periodic motion on halfpipe, aperiodic motion on big air ramp, repetitive balance with BMX, repetitive drive with skateboard, and trick sequence with skateboard. These examples show us that the technology and methodologies can detect different type of sports and skill levels and can identify key factors for successful tricks. These findings are first step toward formalizing action sports science. In future work, wearable devices will be proposed to support action sports training based on the findings with IoT and edge computing technologies.

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