Wearable Real-Time Skateboard Trick Visualization and Its Community Perception

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Motion visualization is an attractive way to provide support for a range of recreational and competitive sports. Hobby athletes can use a visualization of their motion as motivation and to compare their results against those of others. In addition, visualization methods can also be used to present and evaluate high-level performances at competitions, and coaches can establish new training methods and analyze their influence in a visual way.[1]

In skateboarding, the most relevant actions are trick performances. Hence, the visualization of the motion during tricks is of major interest. Pattern recognition algorithms can not only be used to detect tricks for subsequent visualization but can be extended to classify the various tricks performed. Skateboarders, coaches, and spectators can benefit from a system that detects trick performances, provides information about the type of trick, and at the same time visualizes the trick motion, as Figure 1 shows.

Figure 1. Example application of the proposed system. Detected trick events are classified and visualized in real time on a mobile device.

Although applications of such systems could be beneficial for training sessions and competitions, it is important to consider the community's perception regarding the influence of technology on a skills-based activity. Skateboarding and all other board sports (such as snowboarding) highly value the athlete's freedom and individuality, and even in competitions, the subjective perception is relevant for scoring performances. Therefore, we must find a tradeoff between technical involvement and subjective performance measures.[2]

In previous work, Edward Reynell and Hannah Thinyane developed a prototype visualization application that calculates the board's motion using accelerometer data.[3] They incorporated a GPS sensor to provide the GPS location on a map. Sebastiaan Pijnappel and Florian Mueller proposed another trick representation approach that provides a visual 2D presentation of the skateboard's trajectory using infrared emitters attached to the skateboard in combination with a corresponding infrared-sensitive camera.[4] In a survey of skateboarders, Pijnappel and Mueller also obtained information about the required key features for a trick representation.

We developed an extension to the motion representation prototypes that includes a visualization based on the full capacity of inertial-magnetic measurement units (IMMUs). We extended the Reynell and Thinyane study by using gyroscope and magnetometer sensing and provided a 3D representation of the motion that is not limited to a camera-covered area. To augment the feedback provided by the Pijnappel and Mueller approach, we incorporated pattern recognition methods that obtain more information about the performed tricks. Furthermore, we extended their survey with a more general

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questionnaire that explores the skateboard community perception of technological influence in sports.

In this article, we describe the application of our 9D-IMMU-based real-time trick classification and visualization system and report on the survey we conducted. Specifically, we presented our prototype to 27 skateboarders, who then completed a questionnaire about the usefulness, acceptance, and future ideas of such a system.

Real-Time System

The implementation of our proposed system is based on the Kivy programming framework.[5] Kivy is an open source python library that provides a variety of scientific tools. These include scikit-learn,[6] which provides the implementation of a trick classification pipeline, and a GPU-accelerated OpenGL ES 2 graphics pipeline that is used for 3D skateboard visualization. Figure 2 shows a flowchart describing our system's functionality.

Recording Skateboard Motion

Our proposed system collects and transmits data using the Shimmer 3 platform. We attached the Shimmer inertial-magnetic measurement unit to the bottom of the skateboard. Figure 3 illustrates the coordinate system. The IMMU contains a 3D accelerometer (range set to ±16 g), a 3D gyroscope (range set to ±2,000 degrees per second), and a 3D magnetometer (range set to ±0.19 millitesla). The sensor obtains data with a sampling rate of 102.4 Hz and a 16-bit resolution per axis. The acquired data are transmitted to a connected mobile device via Bluetooth in real time.

For the proposed prototype, we defined 11 skateboard tricks, which are explained in Table 1.

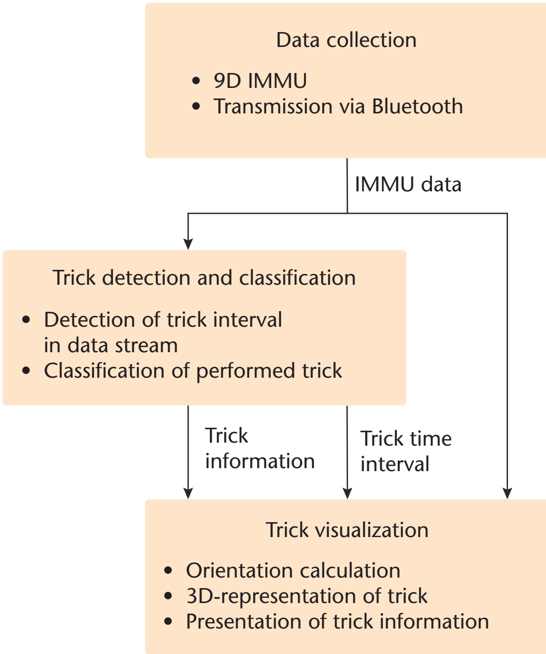

Figure 2. Flowchart of the proposed system. After collecting and transmitting the data in real time, the system detects, classifies, and visualizes the skateboard tricks.

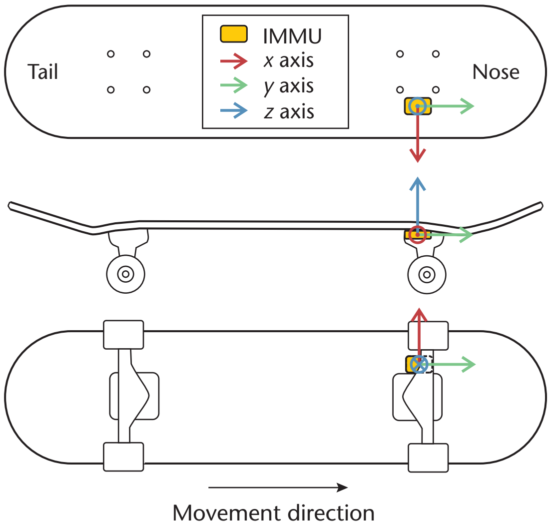

Figure 3. Skateboard sensor coordinate system. A 3D accelerometer, a 3D gyroscope, and a 3D magnetometer attached to the bottom of the skateboard transmit data to a connected mobile device via Bluetooth in real time.

Table 1. Skateboard tricks used in this study.*

Name (abbreviation)	Rotation (angle, axis)
Ollie (O)	Nose liftoff, nose drop (approx. 45° $+x$, approx. 45° $-x$)
Nollie (N)	Tail liftoff, tail drop (approx. 45° $-x$, approx. 45° $+x$)
Kickflip (K)	Counter-clockwise (CCW) about longitudinal axis (360° $-y$)
Heelflip (H)	Clockwise (CW) about longitudinal axis (360° $+y$)
Pop shove-it backside (P-BS)	CW about vertical axis (180° $-z$)
Pop shove-it frontside (P-FS)	CCW about vertical axis (180° $+z$)
360-shove-it backside (360-BS)	CW about vertical axis (360° $-z$)
Varialflip (VF)	Combination of K and P-BS (360° $-y$ & 180° $-z$)
Hardflip (HF)	Combination of K and P-FS (360° $-y$ & 180° $+z$)
Double-kickflip (DK)	CCW about longitudinal axis (720° $-y$)
360 flip (360-F)	Combination of K and 360-BS (360° $-y$ & 360° $-z$)
Bail	Controlled or uncontrolled fall, board does not land on wheels

** The rotation axes refer to the regular stance direction. The gyroscope signals of selected tricks are visualized in Figure 4.*

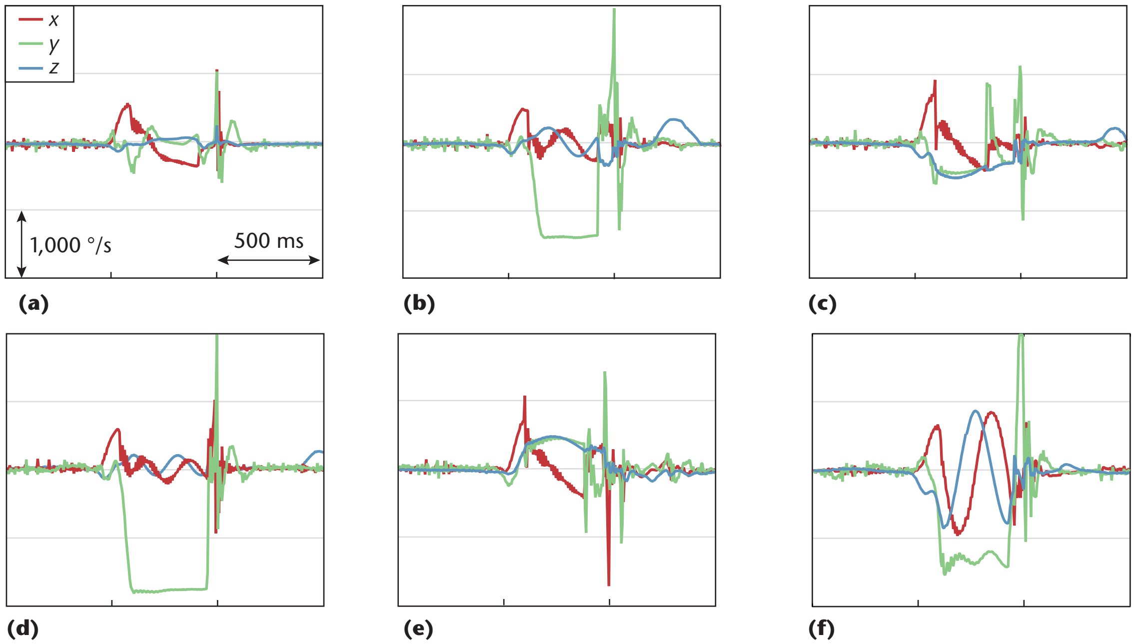

Figure 4. Gyroscope signals of selected tricks: (a) Ollie, (b) Kickflip, (c) Pop shove-it backside, (d) Double-kickflip, (e) Pop shove-it frontside, and (f) 360 flip. Only the gyroscope signals are presented here because they best illustrate the differences between the tricks. However, the proposed system also processes the accelerometer and magnetometer data.

Figure 4 shows the gyroscope signals that correspond to selected tricks. The figure only provides the gyroscope signals because they best present the differences between the tricks. However, the accelerometer and magnetometer data were also transmitted to the mobile device and used by the implemented algorithm. For more detailed trick explanations and videos of these and other skateboard tricks, see www.wikihow.com/do-skateboard-tricks.

Trick Detection and Classification

After the data are transmitted to the mobile device, they are processed in order to detect and classify the tricks performed.

First, a preprocessing step is required to unify the data from the two possible stance directions: regular and goofy. A *regular* riding skater leads with the left foot, whereas a *goofy* riding skater leads with the right foot. According to our previous analysis,[7] the y and z axis signals generated by the skateboard show mirrored behavior for regular and goofy riding athletes. Hence, we invert all the y and z axis signals for all goofy riding athletes before further processing.

To extract the relevant signal intervals for the performed skateboard tricks, the next step is to detect trick events, which requires a continuous incoming data stream in order to identify possible trick events. Figure 5 shows an example of the trick detection procedure. Possible tricks are identified based on the assumption of high acceleration periods at the landing impact after a trick performance. Therefore, we calculate the L^1-norm of the 3D acceleration signal for every time step. All samples that exceed a specified threshold are interpreted as a possible area of interest t_a. Subsequently, the exact time of the landing impact t_{land} is found with the L^1-norm of the derivate of the 3D gyroscope signal. This is based on the assumption that the highest change in angular velocity occurs at the time of the landing impact. Based on previous results,[7] we assume that the period of 1 second before and 0.5 seconds after the landing contains the most relevant information for a trick classification. Hence, we define the trick event interval for further data processing as $[t_{land} - 1\text{ s}]$ to $[t_{land} + 0.5\text{ s}]$.

Lastly, the detected trick interval signals are processed for classification into 13 classes: 11 trick classes (see Table 1), one class for bails, and one rest class for all other detected events that do not contain a trick. As input for the classification, features are extracted based on accelerometer and gyroscope data. These contain the accelerometer's x-z axes correlation after a landing impact (important for the detection of a failed trick); the correlation of the x-y, x-z, and y-z axes gyroscope signals; as well as the rotation per axis during the trick interval based on gyroscope signal integration. We perform the actual classification with a Naive Bayes classifier, which generated the best results in our previous evaluation.[7]

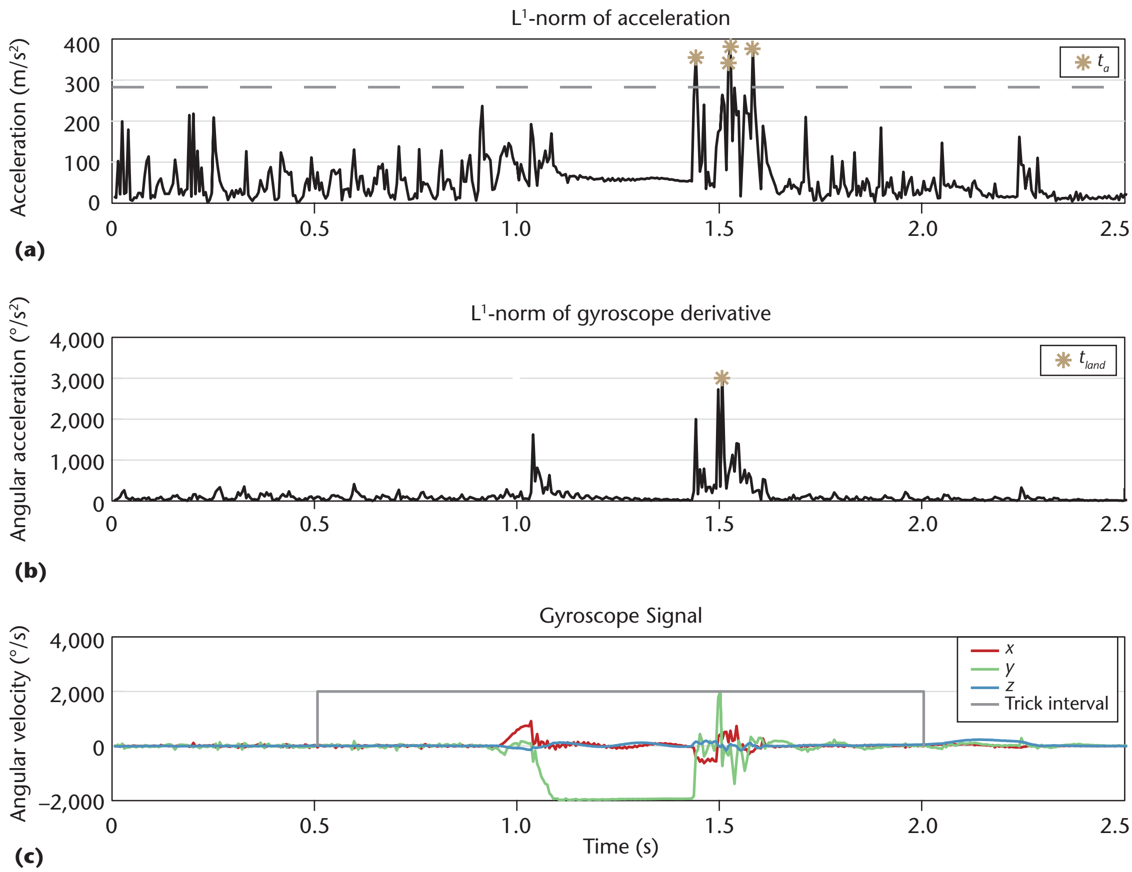

Figure 5. Event detection example. (a) Possible areas of interest t_a are found with the processed accelerometer signal. (b) For the detected areas of interest, the gyroscope derivative is analyzed. The time step with the maximum value of the detected area is defined as the landing time t_{land}. Double detections of one and the same landing time are ignored. (c) The actual trick intervals are defined as between [t_{land} – 1 s] and [t_{land} + 0.5 s].

Visualization

The main application of the proposed system is the visualization of the determined trick information and a real-time representation of the board orientation.

Data fusion for board orientation. To obtain this orientation, we perform a data fusion of the accelerometer, gyroscope, and magnetometer data using the algorithm proposed by Sebastian Madgwick and his colleagues.[8] This algorithm determines the orientation of an object by fusing the acceleration and magnetic measurements. The Madgwick algorithm requires a parameter β that defines the gyroscope measurement error. A lower β leads to a higher influence of the gyroscope in the orientation output.

For the implementation of our work, we defined two different values for β: β_{std} and β_{comp}. Previous measurements showed that the error of the gyroscope measurements is small during standard motion without high-frequency movements. For these scenarios, we use β_{std}. However, at the landing impact after trick performances, the gyroscope signal often exceeds the measurement range that leads to visible deviations in the visualization. These deviations are compensated by a higher influence of accelerometer and magnetometer and thus a lower influence of the gyroscope. Therefore, the second value β_{comp} is activated at every detected landing time t_{land} for an activation duration Δt_{act}. Following the default suggestions in earlier work,[8] we set β_{std} to 0.1 radians per second (rad/s). β_{comp} was defined empirically and set to 0.9 rad/s. The activation duration Δt_{act} was set to 1 s.

Rotation calculation. The output of the adapted Madgwick algorithm is the rotation of the board at each time step provided as a quaternion. This quaternion represents the board's orientation relative to its previous state. To obtain the continuous orientation output, we multiply consecutive quaternions. (See earlier work for the quaternion calculation.[9]) As a result, the skateboard orientation can be visualized continuously for the complete data stream or can be visualized exclusively for trick events by only computing the quaternions of a defined start to the detected end of a trick.

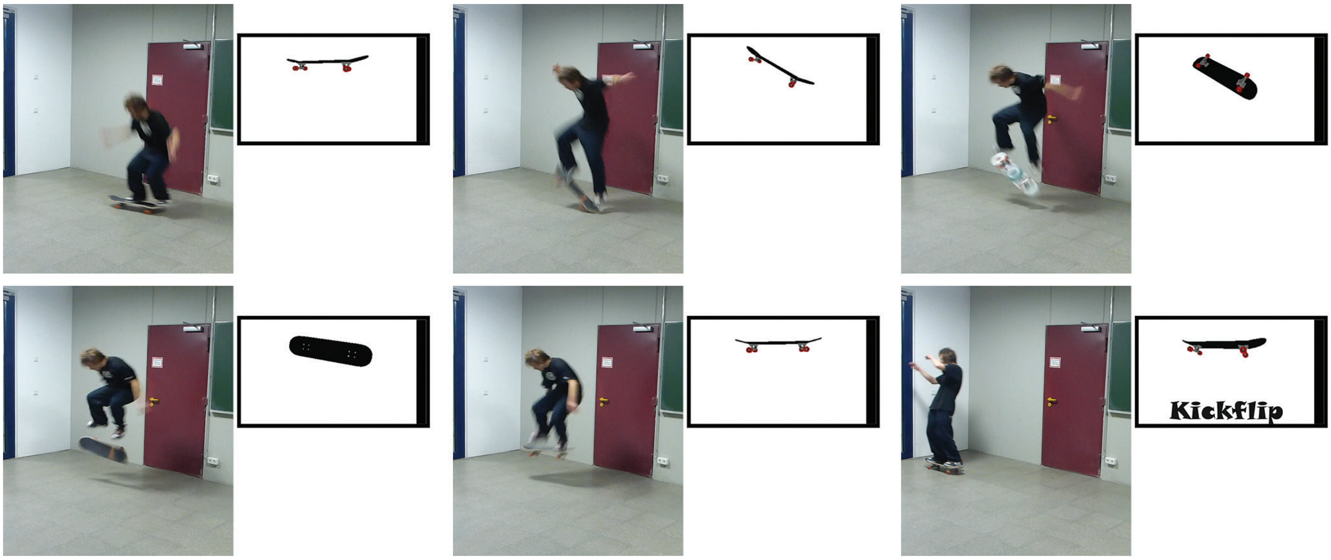

Figure 6. Example sequence of a trick performance and simultaneous visualization. In addition to the 3D visualization of the board rotation, the name of the trick is shown after the classification pipeline successfully detects and classifies the performed motion.

GUI interface. To improve the usability of our application, we designed a GUI visualization based on an object renderer with a basic 3D camera. For this purpose, we use an OpenGL camera implementation of the Kivy framework and loaded and rendered a skateboard model. The skateboard's orientation is updated in every visualization time step based on the calculated quaternion output.

Figure 6 shows an example visualization of a trick sequence. In addition to the rotation visualization, the GUI shows detected and classified tricks after they are processed by the classification pipeline. A video demonstration of the application is available at www5.cs.fau.de/files/skateboard-application.mpg that shows the performance of five skateboard tricks and one bail in combination with the synchronized implementation of classification and visualization.

Community Perception Survey

In skateboarding games and competitions, the subjective perception of the athlete's skill has a major impact on their performance and the judges' evaluations. Hence, we analyzed the impression, observation, and criticism of skateboarders concerning the influence of technology in their sport by conducting a survey. Specifically, in our survey we evaluated three topics:

- *Reactions to the proposed system*. We introduced the proposed system to the skateboarders by showing them the trick visualization video footage at www5.cs.fau.de/files/skateboard-application.mpg. We then asked the skateboarders questions regarding the likability of the visualization of the tricks, the usefulness of such a system, and possible improvements.
- *Opinion about feedback systems*. The participants were asked if skaters would like to know how they could further improve their skating skills, at what point in time such feedback is desired, and if such feedback should be available with adaptive speed (such as in slow motion).
- *Technical systems in sport*. The participants were asked questions regarding the fear of a possible overpowering of technical systems, possible application fields of technical systems in sports (such as in games and competitions), and the possibilities for a multiplayer mode.

The survey responses to these questions were provided using a seven-point Likert scale, where a 1 indicated "strongly disagree" and 7 "strongly agree."

In total, 27 athletes participated in our survey, with an average age (in years) of 23.2 ± 4.4 and an average (in years) of 10.0 ± 4.9 of skateboarding experience. Figure 7 gives their responses to the survey questions. The plots show the median of the selected answers as well as the 25th and 75th percentiles. In addition, we calculated the participants' overall agreement rate (voted with a 5 or higher) and disagreement rate (voted with a 3 or lower) for each question.

Furthermore, the participants suggested the following areas of possible improvement:

- visualization of body and foot movement,
- determination of total rotation angle and air time,

- measurement of force applied to the board,
- incorporation of multiple perspectives, and
- establishment of training application.

Discussion

The participants perceived the trick visualizations as generally comprehensible and clear. Furthermore, a majority of the participants rated the application as reasonable and useful. However, with a median rating between 5 and 6, there is still room for improvement.

A body and foot representation would be feasible with further sensors attached to the athlete's body. In addition, the usefulness of the application could be improved by providing further relevant information, such as the overall rotation and air time.

Among skateboarders, there is a noteworthy high demand for feedback on their performances. One indicator of this is that more than four-fifths of our participants wanted to be able to see their tricks performed in slow motion. Another indicator is that they preferred to have feedback about their performed tricks right after or within a few minutes of completing the trick. These results indicate the usefulness of a sensor-based system and point out its advantages over other trick analysis methods, such as video recordings and delayed feedback from more experienced skaters.

An essential topic for further research is the acceptance of computer-assisted systems. Only a minority of the participants in our study feared that technical systems might invade the board sports domain. In contrast, many participants believed that innovative methods could provide support at competitions. However, almost all the participants agreed that a machine-based judgment could never replace human judges.

We have demonstrated the feasibility of an informative real-time trick visualization in skateboarding, and the results of our survey indicate that computer-assisted support for skateboarding is well received by most skateboarders. However, our study also shows that some participants are still skeptical about the influence of technology in skateboarding. This outcome underlines the importance of the subjective human factor in board sports. Hence, although further research in this field would be supported by many skateboarders, the importance of the subjective component and the athlete's individuality should always be considered.

Future research on feedback systems could include the extraction of further relevant information such as the overall board rotation, air time, and applied forces. An extended visualization should include a representation of the athlete's body and feet. Although the conducted survey clearly indicates the acceptance and usefulness of a feedback system, an extended study with a real-time feedback application could possibly receive an even better community perception.

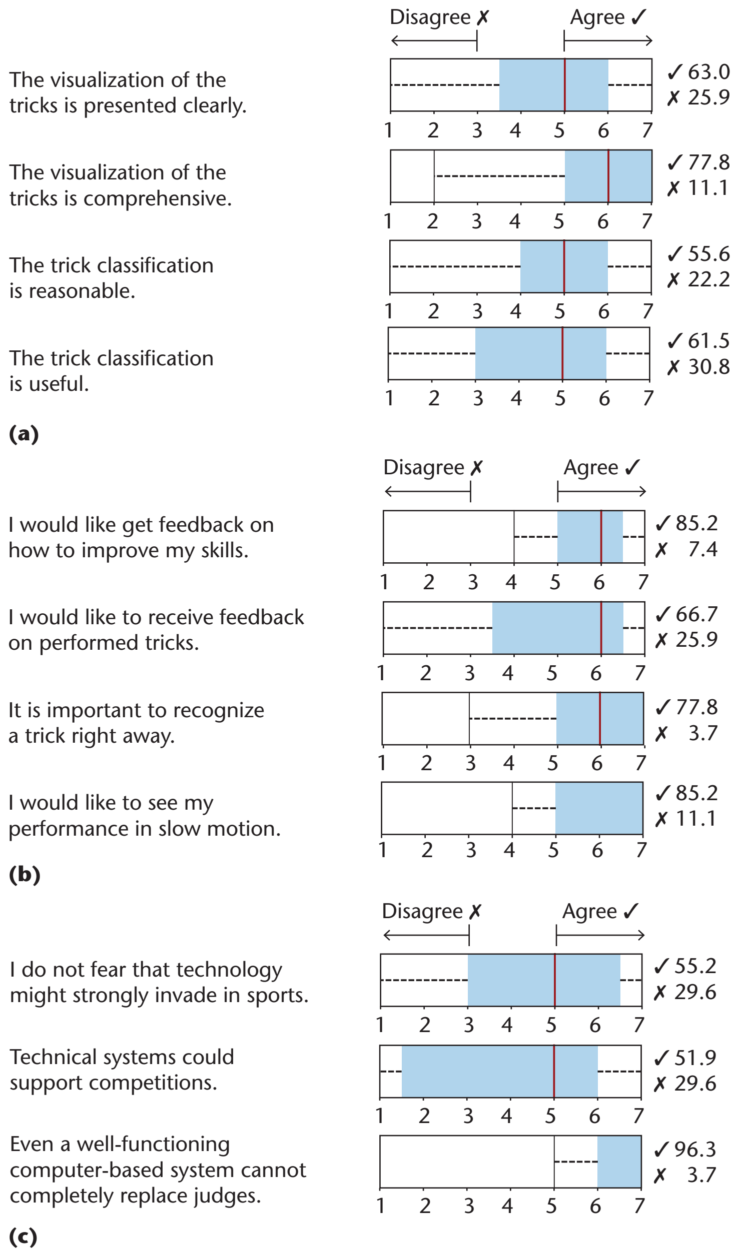

Figure 7. Survey questions and answers: (a) reactions to the proposed system, (b) general opinion about feedback systems, and (c) technical systems in sport. The box plots show the median (red line), 25th and 75th percentiles, and a whisker with the maximum of 1.5 times interquartile range (dashed lines). The percentages to the right of the plots show the overall agreement (selection of a 5 or higher) and disagreement (selection of a 3 or lower) rates for each question.

Acknowledgments

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