Near-Realistic Mobile Exergames With Wireless Wearable Sensors

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***Abstract*—Exergaming is expanding as an option for sedentary behavior in childhood/adult obesity and for extra exercise for gamers. This paper presents the development process for a mobile active sports exergame with near-realistic motions through the usage of body-wearable sensors. The process begins by collecting a dataset specifically targeted to mapping real-world activities directly to the games, then, developing the recognition system in a fashion to produce an enjoyable game. The classification algorithm in this paper has precision and recall of 77% and 77% respectively, compared with 40% and 19% precision and recall on current activity monitoring algorithms intended for general daily living activities. Aside from classification, the user experience must be strong enough to be a successful system for adoption. Indeed, fast and intense activities as well as competitive, multiplayer environments make for a successful, enjoyable exergame. This enjoyment is evaluated through a 30 person user study. Multiple aspects of the exergaming user experience trials have been merged into a comprehensive survey, called ExerSurvey. All but one user thought the motions in the game were realistic and difficult to cheat. Ultimately, a game with near-realistic motions was shown to be an enjoyable, active video exergame for any environment.**

***Index Terms*—Activity monitoring, exergaming, user experience, user survey, wearable sensors.**

I. Introduction

EXERGAMING has emerged as a potentially valuable tool of wireless health to help with regular exercise for healthy individuals [1], collect health information [2], and help as treatments for rehabilitation [3]. Obesity [4]–[6] is of particular importance, becoming a significant health burden and impacting world-wide economies [7], [8]. This trend has the potential to increase the obese population by 33% and severely obese population by 130% in the United States alone [7] by 2030, resulting in a population of which at least half are obese [9]; such a cost, if curbed over the next 20 years, can save the U.S. economy almost $550 billion in medical expenditures. Children are becoming significantly more overweight and obese as a result of sedentary behavior associated with television and video games [10]–[12]. As a result, pervasive sensing technologies to monitor physical activity have become increasingly prevalent [13], particularly through the usage of body-wearable sensor networks [14]–[16]. This has led to the usage of these accelerometer systems particularly to provide input from the human body to video games [17].

Exergaming, through the use of pervasive body-wearable sensor or camera-based systems, has been further evaluated to see if it can reduce sedentary behavior and increase exercise in children and adults alike, both healthy and obese [6], [18]. Indeed, exergaming achieves light-to-moderate physical activity [19] and impact overweight children [20]. Lately, work has emerged showing a guaranteed level of energy expenditure in exergames, good for healthy adults as well as obese children [21], by monitoring activity levels through accelerometers attached to the body.

As the field expands, the use of mobile technology to assist in the development of exergames has grown [22], [23]. This ubiquitous nature of gaming is important to expand the use from both a multiplayer environment as well as an immersion environment. Such games allow for better interaction with others as well as incorporating the real world into the game to increase the enjoyment. These mobile games, however, often use the mobile device for controller input and thus, do not provide a realistic gaming experience. When evaluating what makes a successful exergame, one must consider the elements necessary. Those seem to be the requirements of fast, intense activities [24] as well as an enjoyable experience that does its best to mask the exertion through the usage of a multiplayer setting as well as the appropriate set of activities [25].

This study attempts to unify several fragmented exergaming ideas into one system development for successful exergaming work. First, unlike previous work, this paper will present a soccer exergame developed based on movements set in reality instead of mapping moves to preexisting games. This study will first take a realistic sports environment and attempt to translate it into a ubiquitous game platform by collecting an appropriate soccer dataset. Furthermore, this study will present a truly pervasive platform for mobile exergaming with near-realistic motions through wearable sensors. The fast, intense exercises will provide caloric expenditures and create a level of enjoyment through the gaming platform. This study will be evaluated from an algorithmic context with regards to the precision and recall of the activity system, as well as present a qualitative result with the use of a 30-person user experience study. This information is then presented in a structured format to assist in the development of future mobile sports exergames.

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II. Related Works

A. Exergames

Several exergaming solutions target full-body motion gaming [1], [4], [26]. Work by Gerling *et al.* [26] developed a full-body motion-based game with four static gestures and four dynamic gestures. The goal of this study was to develop a fun game for adults based upon the Kinect platform. Such a platform, however, is limited to the environment and region the camera can caption, and as a result, is not a truly mobile system with intense activities. Further, work in [27] surveys Kinect and other camera-based motion tracking and points to potential lighting change problems in certain recognition systems. As a result, this paper will use wearable sensing to capture the activities.

Work by Park *et al.* [1] introduced a competitive exercise-based game. Users performed actions on a stationary bike, with a jump rope or a hula-hoop in order to race each other in teams of two. Authors used a motivating scenario of taking standard exercise mechanisms and applying a gaming environment to them to make the games more enjoyable. While this is a great way to encourage adoption of such a platform, ultimately the actions do not correlate with the gaming environment movements. This paper builds upon such an idea by taking actions that map directly to games to create a virtual soccer environment based upon a realistic one. Work by Mortazavi *et al.* [21] guarantees that these actions will achieve moderately intense exercise levels.

Work by Mortazavi *et al.* [4] involved creating a realistic soccer exergame based upon a gaming platform. Using wearable sensors to create a pervasive controller, this study showed creating intense exercise, and guaranteed a level of realistic motions, created an enjoyable interface for existing soccer games. This study builds upon the idea of creating a realistic sports gaming environment. However, instead of mapping to an existing game, this study will delve into creating a new game for an experience that immerses users in the game completely. For example, the soccer exergame presented maps to FIFA 10 [4]; however, no defensive moves are recognized, most likely due to the inability of users to constantly slide tackle in place. This study will expand upon that as well as develop a more comprehensive survey, considering the same cheating and near-realistic techniques involved.

B. Mobile Exergames

Mobile exergames, meanwhile, tend to fall into the realm of being a health game on a mobile platform [2] or games in which the mobile platform is the controlling mechanism for the exergame [28], [29]. While work by Grimes *et al.* [2] introduced a new realm in exergaming by developing a ubiquitous, mobile platform, where the gameplay itself does not require any exercise. The other games, which use the mobile device as the controller have limited motions since the location and direction of movement are considered the important input [28], [29].

Work by Wylie and Coulton [30] used wearable sensors to help enable persuasive mobile exergaming. Their work considered measuring the heart rate of a user in order to motivate both running movements in and around locations in order to defend a healthy heart from attacks of viruses. This study incorporates pervasive sensing technologies and realistic running with exergaming. As a result, this study falls short in developing a platform for many kinds of realistic motion-based exergaming, but is one that validates it as an area of research.

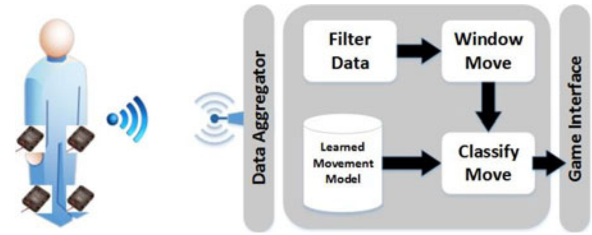

Fig. 1. Full mobile exergame system with wireless body area network of sensors with data aggregator and classification system for gameplay.

III. System Description

This section describes the methodology involved in developing a tablet-based mobile exergame with wearable-body sensors as shown in Fig. 1. The development of a soccer exergame based upon realistic motions took several steps. The first step was to determine the movements necessary to make a realistic game. For example, when training on an actual soccer field, players are taken through a practice process in which they run from place to place on a field and perform certain actions, such as passing or shooting. Based upon this idea, this study presents a gaming framework based upon realistic sports scenarios in order to develop a directly realistic comparison between gameplay and a real sports environment. In this case, an obstacle course-like soccer game with soccer actions is such an environment. After collecting a comprehensive soccer dataset, movements were selected and used for training a recognition algorithm. Then, an appropriate evaluation of such a game is necessary. This evaluation should be twofold. The first method should analyze the accuracy of such a recognition system, and use this information to generate health statistics. The second is to gather user input on the finished product, since, ultimately, such a game needs to meet certain features in order to be adopted as an actual exergaming solution [24], [25].

A. Dataset and Creation

A full list of soccer movements collected from users is shown in Table I with all their descriptions, referenced from the right foot. These data were collected using a Memsense Wireless IMU (Inertial Measurement Unit), attached to the right shoe. This device contains a 5-g triaxial accelerometer, 600°/s gyroscope, and a magnetometer for a total of nine degrees of freedom, and operates at 100 Hz. All nine sensor readings are combined in a single packet of information transmitted at 100 Hz, so that each reading has 9 values per point in time. Twenty-four users collected ten repetitions of each movement. These movements were selected because they spanned the realm of offensive soccer movements, with multiple types of passes and shots, along with a few trick plays.

TABLE I
FULL-LIST OF SOCCER MOVEMENTS

Movement	Description	Approx. Duration	Retained in Final System
Back Heel	Pass backward	.5s	*
Behind Foot Pass	Pass left behind left leg	.75s	*
Square Pass	Pass left (standard)	.75s	*
Through Pass	Lead pass forward and left	1s	*
Flick Pass	Quick pass to right with outside of foot	.5s	*
Chip/Lob	cross a ball forward and to the left in the air	1.5s	*
Fake Shot	Fake shot (only backswing)	.75s	*
Full-Swing Shot	Full powered swinging strike	2s	*
Medium Powered Shot	Strike ball with laces (minimal backswing)	1.5s	*
Quick Shot	Toe poke quick release (no backswing)	.5s	*
Curved Shot	Placed shot, using side of foot	1.5s	*
Cut Left	Running motion, step right cut to left	2.5s	
Cut Right	Running motion, step left cut to right	2.5s	
Side Step	Step on ball, roll it to the right	1.5s	*
Spin Move	360 degree spin move with ball	2.5s	
Step on Ball	Stopping ball in place	.5s	
Step Over Ball	swing leg around ball, never touching it	1s	*
Run	Running in place	1s	*
Sprint	Sprinting in place (at least double the speed of run)	.5s	*
Walk	Stepping forward	1s	

A short-duration game in which users must run between obstacle courses and then participate in a given action mimics the simulated gameplay work conducted by Mortazavi *et al.* [21], in which a guaranteed moderate level of physical activity is measured in a simulated soccer exergame situation. With that in mind, a subset of these movements was selected for the game, as they were deemed necessary for a game that would stand in place.

B. Recognition

In order to develop a game around these movements, a recognition system must be built first. As stated earlier, the system in this study is extended from work by Mortazavi *et al.* [4] for a soccer exergame. This system uses a nearest neighbor technique for a few movements off of mean templates of movements. Due to the increased number of classes, and the similarity of some of these movements (e.g., the square pass versus the through pass), a gyroscope was added to each sensor in the system in order to provide more information for each movement.

1) Developing Mean Templates for Training: After all the data were run through a moving average filter (of length 20 points—selected to allow highest classification accuracy), each movement was analyzed in the training set and a window size of 300 points was initially selected to encapsulate each movement. The training set was manually annotated with the midpoint of each move. Thus, any window size that incorporates the midpoint is important and adjustable window sizes are possible. For example, a spin move might take the full 300 points but a pass might only take 120. However, the individual actions have no immediate movement around them, so filling the window to 300 points does not alter the activity recognition greatly. Given a particular window size, a vector can be made of each movement in which each channel of data is concatenated together

$$\mathbf{m} = \langle \mathbf{a_x}, \mathbf{a_y}, \mathbf{a_z}, \mathbf{g_x}, \mathbf{g_y}, \mathbf{g_z}, \|\mathbf{a}\|, \|\mathbf{g}\| \rangle \tag{1}$$

where each component, such as $\mathbf{a_x}$, is the window-sized time-series vector for that axis of acceleration. A vector for the move is created from each sensor on the body. Finally, the final two channels in this eight-channel signal are the magnitude of the acceleration and the magnitude of the gyroscope, calculated as

$$\|\mathbf{a}\| = \sqrt{\mathbf{a_x}^2 + \mathbf{a_y}^2 + \mathbf{a_z}^2} \tag{2}$$

$$\|\mathbf{g}\| = \sqrt{\mathbf{g_x}^2 + \mathbf{g_y}^2 + \mathbf{g_z}^2}. \tag{3}$$

Once an individual move m is arranged, each training example is ordered and a mean-template for each move is created

$$\mu = \left\langle \frac{1}{n}\sum_{i=1}^{n} \mathbf{a_{xi}}, \frac{1}{n}\sum_{i=1}^{n} \mathbf{a_{yi}}, \ldots \right\rangle \tag{4}$$

where each component in the vector is the associated index in vector $\mathbf{m}$ and each i is a training example from the training set. For example, if the moves are 300 points by eight channels, then μ is a 300 point, eight-channel signal averaged over the range of i training examples. Thus, the training set becomes

$$\text{Training} = \{\Theta_j | j = 1, \ldots, 15\} \tag{5}$$

where each j represents one of the 15 moves in this training set, and

$$\Theta_j = \{\mu_1, \mu_2, \ldots, \mu_s\} \tag{6}$$

Θ_j represents the set of means for an individual move across each of the s sensors worn on the body (e.g., s could be 4, for a sensor on each limb).

2) Classification Algorithm: Once the training set is created, the online classification algorithm runs. This is based on a nearest neighbor algorithm in which each move is evaluated and compared against the average movements stored. A sliding window of size w is set, where w is the same size used in the training set above. The window overlaps point by point. This is because a Euclidean distance will result in a large gap until the windows line up well. This allows for the move to center nicely in the window to be classified correctly. Two factors in classification change from work by Mortazavi *et al.* [4]. First, with the addition of the gyroscope, the velocity comparison is removed, primarily to reduce computation time in the mobile environment. Furthermore, work from Mortazavi *et al.* [21] shows that the energy expenditure calculations for each movement in a soccer exergame provide a formula to guarantee intensity. This calculation was used for both health information and for the cheating prevention that was velocity-based in previous work. Once the sliding window adjusts for the new point, the euclidean distance between the point and the mean-templates are calculated, and a class is selected

$$d(\mathbf{m}, \mu) = \|\mathbf{m} - \mu\| = \sqrt{\sum_{w} (m_w - \mu_w)^2} \tag{7}$$

and then an overall distance value D is calculated as a weighted sum of the distances between each sensor template as in

$$D = \sum_{i}^{k} p_i \times d(\mathbf{m}, \mu_\mathbf{i}) \tag{8}$$

where the weights, p_i, are adjustable if particular limbs are more important for some movements over the others. Finally, with this overall distance value, a class can be selected where:

$$c(m) = \{\text{class}(\Theta_j) | \Theta_j = \underset{j}{\text{argmin}}\{D(m, \Theta_j)\}, D < \tau\} \tag{9}$$

where c is the class of template Θ_i, $D(m, \Theta_i)$ is the euclidean distance between each sensor of move m and each sensor mean μ_i of the template move Θ_i that results in the minimum distance. This distance must be smaller than a predefined threshold τ or the movement is simply considered as no class. This τ is adjustable based upon the distance and the energy expenditure calculated [21], and can be altered given the intensity desired in the final application. In a system with multiple sensors, each sensor runs such a classification. A majority voting scheme is used to determine the classification result and in the event of a tie, the foot sensor on the right foot makes the ultimate decision as the game in this paper is primarily based upon movements of the right foot.

C. Improvement With PCA

As the number of movements and classes increases, a more robust algorithm is needed aside from the mean templating presented. An obvious expansion from the mean templating is to use those templates and determine the eigenvectors and eigenvalues of the system and run a principal component analysis (PCA). Then, each move window is decomposed and reconstructed with the top eigenvectors and the minimum reconstruction error results in the chosen class.

1) Model Generation: A window around each of the channels of data is selected to create a fixed-sized move similar to above. Then, the training system calculates the mean for each of the channels. If m moves are represented as c-channel vectors, then the mean move is a component-wise mean, as in

$$\mu = \left(\frac{1}{m} \sum_{i=1}^{m} \mathbf{x}_{1i}, \frac{1}{m} \sum_{i=1}^{m} \mathbf{x}_{2i}, \ldots, \frac{1}{m} \sum_{i=1}^{m} \mathbf{x}_{ci} \right) \tag{10}$$

where the sum of the $\mathbf{x}_j$ are the sums of window size w vectors $\mathbf{x}_j$, where, in this system $\mathbf{x_1} = \mathbf{a_x}$, $\mathbf{x_1} = \mathbf{a_y}$, and so on. The mean template, μ, is a c-channel signal of the same window size, w, as each of the individual moves. The PCA of each move is run, using the sorted order of eigenvalues to find the most significant eigenvectors. Thus, the training set consists of a mean move μ and a set of eigenvectors e_i per μ, across all moves.

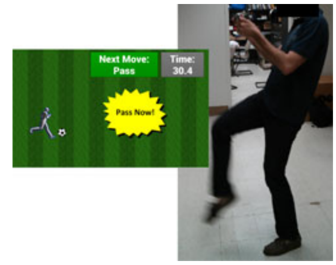

Fig. 2. User from trial playing the mobile soccer exergame (left).

2) Activity Recognition: The models generated are made over various window sizes and are stored. Each is then used during the classification processes. To classify a move, a w-sized test window is decomposed and reconstructed using the top k eigenvectors and the mean μ for each of the training moves. The number of eigenvectors can be chosen based upon the performance and speed, and as such, ten are chosen for this particular application. The Euclidean distance between the original test move, $\mathbf{x}$, and the reconstructed move, $\mathbf{r}$ is calculated as

$$err\left(\mathbf{x}, \mathbf{r}\left(\mu\right)\right) = \|\mathbf{x} - \mathbf{r}\left(\mu\right)\| = \sqrt{\sum_{i} \left(x_i - r_i\left(\mu\right)\right)^2} \tag{11}$$

where i represents each channel of the data, (e.g., eight in this case), and $\mathbf{r}$ is a function of μ and its associated eigenvectors. This reconstruction error is computed over all of the training means μ and their associated eigenvectors. To classify a move $\mathbf{x}$ of type C based upon the minimum error, the class with minimum reconstruction error is chosen, as in

$$C\left(x\right) = \left\{ \text{class}\left(\mu\right) | \mu = \underset{\mu}{\text{argmin}} \left\{ \text{err}\left(x, r\left(\mu\right)\right) \right\} \right\}. \tag{12}$$

If a single μ is returned, then simply classify move x as the same class as the mean move μ. In the event that a subset of two or more classes of moves results in the same minimum reconstruction error; then, the classifier randomly chooses the class from this subset of moves.

D. Implementing on Mobile Device

The game was developed as a side-scrolling field. As the user runs, he/she approaches each action node, a prompt appears to complete the action, as seen in Fig. 2. As the action is completed, the field will scroll and the next movement is indicated, with the current move indication disappearing. The scrolling field and movement indicators are how the user knows that the actions are being performed. Based upon how well the users are able to complete the actions they are giving a final time score, intended to encourage competition. The game was developed on the Android development platform for a Nexus 7 tablet (quad-core with 1 GB of RAM). Several computational adjustments needed to be made in order to guarantee a real-time and intense experience. A tradeoff between multithreading the classification and running each sequentially must be analyzed on a case by case basis to avoid delay. Too many threads causes too much context switching, particularly because the Bluetooth-enabled sensor is transmitting at 100 Hz. Too few and the number of moves must be reduced. This is ultimately how the limit of 15 moves was selected for this game. The game was targeted at being around 3 min per round, so that it could be played quickly if needed, or repeated to make a longer gaming experience. Running between each action guaranteed around seven metabolic equivalents [21], [31] of energy expenditure, being light to moderate intensity activity.

E. Survey Creation

In order to evaluate the success of such a game, three aspects must be analyzed. The first is the recognition algorithm, the second is the measurement of caloric expenditure, and the third is a user experience trial to determine if such a game can achieve the tasks desired. However, determining the appropriate requirements for a user survey might not be immediately obvious. Several works discuss the need to have the right set of questions depending on the goal. These works consider the appropriate techniques to evaluate user experience for gaming environments [32], [33], namely:

1) multiplayer approach [34];
2) fast, intense, accurate motions [24];
3) encouragement of physical activity [35], [36];
4) focusing on details of gameplay [35];
5) realism and cheating prevention of exergames [4];
6) health Information [4];
7) comparison to other games and general enjoyment [4], [33].

In that light, this study presents ExerSurvey; an initial attempt at developing a comprehensive, unifying survey for user experience trials for future exergame work and user experience research. This survey attempts to address each category, where each category is generally ranked from 1 to 5, where 1 would be very bad and 5 very good. First, general statistics are collected regarding whether they have played video games, mobile video games, the sports, or those video games related to the sport. Then, how often the users exercise, to gauge their general level of physical activity. Questions on each related category (the scoring for those not immediately obvious will be listed after the question) are:

1) *Enjoyment of Games:*
   - Q1) Enjoyment of Comparison Games;
   - Q2) Enjoyment of Mobile Exergame;
   - Q3) Enjoyment of Exergame Over Comparison Game (1. great prefer standard game, 2. prefer standard game 3. neutral 4. prefer exergame, 5. greatly prefer exergame);
   - Q4) Enjoyment of Exergame over Motion Input to Comparison Games (1. great prefer mobile motions, 2. prefer mobile motions 3. neutral 4. prefer exergame, 5. greatly prefer exergame).
2) *Statistics Regarding Exergame*
   - Q5) Perceived Accuracy of Exergame;
   - Q6) Level of Fatigue (1. great fatigued, 2. fatigued 3. neutral 4. rested 5. completely rested);
   - Q7) Realism of Exercise;
   - Q8) Ability to Cheat Game (1. Don't have to perform actions 2. Easy to avoid most actions 3. neutral 4. almost impossible to cheat 5. absolutely impossible to cheat).
3) *Enjoyment of Games*
   - Q9) How often per week would you play standard mobile games?
   - Q10) How often per week would you play mobile exergames?
   - Q11) How did you perceive the duration of the game (1. way too short 2. too short 3. about right 4. too long 5. way too long)?
4) *Multiplayer Aspects*
   - Q12) How well does the scoring motivate you?
   - Q13) How do the multiplayer aspects of the game affect your opinion?
5) *System Goals*
   - Q14) How helpful was the health information provided?
   - Q15) How did you feel about the sensor system?
   - Q16) How would you rate the mobility of the game?
   - Q17) How would you rate the intensity of activity reached?
   - Q18) How well did the exergame achieve its intended goals?

IV. Results

The mobile soccer exergame developed was evaluated on 30 users, six females and 24 males, age ranging from 18 to 58, with varying levels of experience in video games, soccer, and mobile games. One sensor was used, and after attaching the sensor to the user's right foot, users were given three games to play. Users were shown all the movements and then were given a minute to practice and ask questions before playing the games. Those games were EA Sports' FIFA 10 on the tablet played with the simulated joystick, played with tablet controls (using the accelerometer for running by tilting the tablet), and the soccer exergame developed in this paper with PCA as its classification method. The order in which they played the game was randomized. They were allowed to play the game in any environment they desired (e.g., a lab, a park, an apartment, etc.). Each half of FIFA was set to 4 min and the soccer exergame took about 3 to 4 min to complete, depending on the user's abilities. After playing each game, the users were given the survey. The short duration of the game, while not ideal for prolonged exercise, mimics many user's behaviors with mobile games that can be played in any environment with any break during his/her day or repeated if desired. Health statistics were calculated by the method in [21].

A. Classification Results

A leave-one-person-out cross validation was used on the training set in order to test the accuracy of the algorithm, for both the mean template and for PCA. It was compared with a common general daily-activity monitoring system, that extracts from a movement window the mean, standard deviation, power, and

TABLE II
PRECISION, RECALL, AND F-SCORE, RESPECTIVELY, OF MOBILE SOCCER EXERGAMING SYSTEM USING A SUBSET OF MOVEMENTS AND FULL SET VERSUS A GENERAL-ACTIVITY MONITORING SYSTEM [37]

Algorithm	Subset of moves [4]	Full set of moves
PCA	89%, 89%, 89	77%, 77%, 77
Soccer [4]	81%, 80%, 80	63%, 61%, 62
General Activity [37]	66%, 41%, 51	40%, 19%, 26

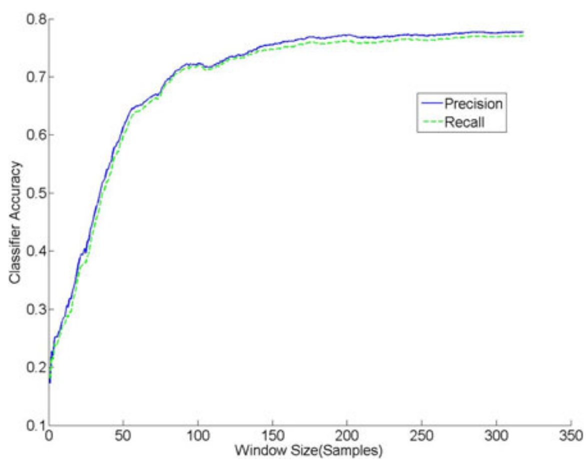

Fig. 3. Accuracy versus window size.

correlation across each axis and supplies this information to a support vector machine, as in work by Ravi *et al.* [37]; the classification results are shown in Table II. The results show that the algorithm with the gyroscope added is very strong for the movements used in Mortazavi *et al.* [4] and while it diminishes a bit on the full set of movements selected, it significantly outperforms the general daily-living activity system, showing the need for gaming movement-specific classification algorithms. As seen in Fig. 3, the precision and recall reaches a high level a little over half-way through the window. Since each move ranged between 80 and 300 points, the window size was dropped to 200 points. This is because the last 100 points of activity are generally the user's foot returning back to the ground, and so, do not provide a significant classification difference; however, the reduced window size gives an extra second with which to compute the classification and give the user more responsive behavior. This result can be measured in the perceived accuracy, realism, and cheatability of the game as measured in the survey.

B. Survey Results

The entire user survey is shown in Table III and the results are generally positive. The users felt the system was accurate, realistic, generated exercise, and was hard to cheat. In particular, the categories under the scores of 3 all still show signs of being appropriate given the scenarios presented. For question 1, users did not seem to like the control scheme for FIFA on the tablet. For question 6, the rating just under 3 indicates users feeling slightly fatigued when playing the game, a desirable outcome (the survey should be corrected to make this a score of 4, a desirable outcome). Question 10, while indicating users would likely only play this game a few times a week, has a rating higher than Question 9, which indicates how often they would play FIFA in a mobile setting. Question 11 indicates the game should be extended in length, a simple parameter to adjust. Question 12 shows that the timing score did not motivate users, showing the need for a better feedback mechanism; however, the same score still drove multiplayer competitiveness, as shown in question 13. Finally, question 14 was listed as not-applicable due to its addition to the survey after the trial had begun. Wii and Kinect FIFA were not used because the game on each console uses standard controls.

V. DISCUSSION OF USER EXPERIENCE TRIAL

The mean results of most questions were 3 or higher. In particular, only several questions had a mean score of 2.5 or below. As a result, the survey shows a fairly consistent experience, with obvious room for improvement. The lower results with lower mean and higher standard deviation, related to the classic FIFA game, the lack of fatigue playing the exergame, and the short duration of the exergame. The former is a beneficial result while the latter two show the need to build a more complex game, as will be discussed in Section V-E.

A. Enjoyment of Games

First and foremost, users must enjoy a game, otherwise it will not be adopted. As already demonstrated in Table III, users enjoyed the exergame. Those that had a higher experience playing soccer exergames were more demanding; however, they still thoroughly enjoyed it. As shown in Fig. 4(a), most users either enjoyed both games or thoroughly enjoyed the exergame. The few users who did prefer FIFA all indicated that they played some form of the mobile FIFA game on a consistent basis. However, when asked if they preferred the exergame's motions, the survey results were generally stronger, with users indicating that they preferred using their body to tablet motion for movement. Participant P4, for example, who considers himself an experienced video gameplayer and soccer player, indicated that

> "The Exergame was better than FIFA. In particular it motivates movement and physical activity (especially using the foot) is very exciting."

P10, a 32-year old male who plays a lot of video games, soccer video games, and mobile games but is not an actual soccer player, and states

> "The movements of the exergame were more applicable to actually playing. Moving the tablet just seemed like an awkward way to control players."

B. Exergaming Accuracy

Fig. 4(b) shows that the system was deemed generally fairly accurate, though a little more neutral than one would desire. One can infer from the score question (question 12) having a mean under 3 that the system did not produce enough feedback with regards to the specific actions. Furthermore, it became apparent that the cheating prevention aspects of the activities, the specificity and intensity required to perform the actions realistically, were hampering the perceived accuracy of the system. As shown

TABLE III
AVERAGE SCORES AND STANDARD DEVIATIONS FOR THE 18 QUESTION EXERSURVEY GIVEN TO ALL 30 PARTICIPANTS

Q. 1	Q. 2	Q. 3	Q. 4	Q. 5	Q. 6	Q. 7	Q. 8	Q. 9
2.97 ± 1.16	3.50 ± 0.90	3.60 ± 1.04	3.93 ± 0.98	3.47 ± 0.94	2.90 ± 0.71	3.67 ± 0.55	4.13 ± 0.82	2.23 ± 1.19
Q. 10	Q. 11	Q. 12	Q. 13	Q. 14	Q. 15	Q. 16	Q. 17	Q. 18
2.40 ± 1.07	2.77 ± 0.86	2.83 ± 1.09	3.77 ± 0.77	N/A	3.27 ± 0.87	4.13 ± 0.73	3.13 ± 0.82	3.50 ± 0.82

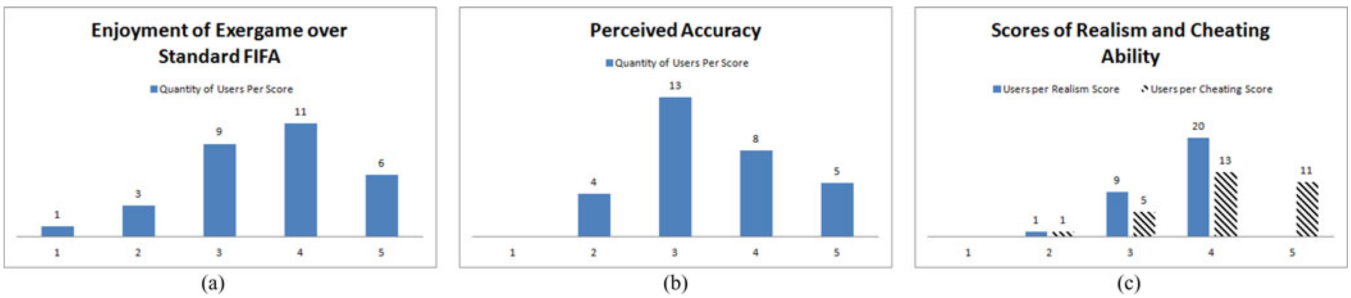

Fig. 4. Quantity of Users per Score Category in (a) preference (b) perceived accuracy and (c) realism of controls and ability to cheat that realism.

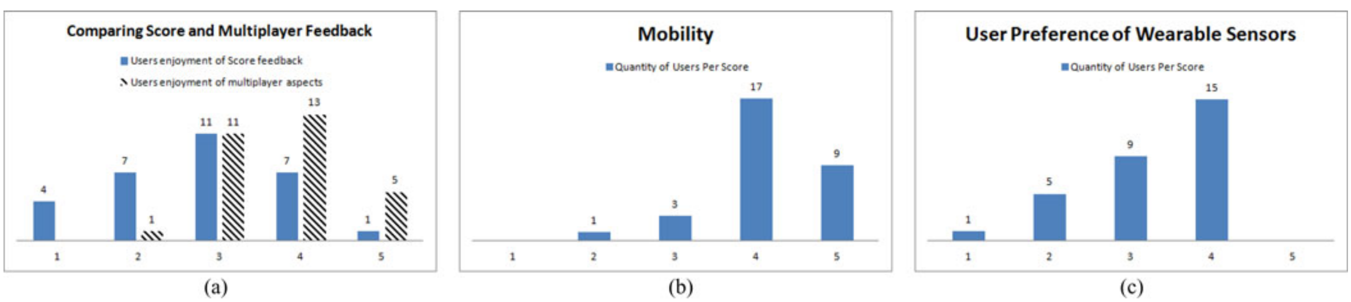

Fig. 5. Quantity of users per score for (a) perception of benefit to scoring and multiplayer information (b) mobility of the system and (c) perception of pervasive sensor system. (a) Scoring and Multiplayer Aspects. (b) Mobility of System. (c) Sensor System.

in Fig. 4(c), the system was generally considered near impossible to cheat and the actions very realistic. Future exergame work must do a better job providing direct feedback to each action, so that the user knows whether the system is inaccurate or if she/he is performing the action incorrectly, as was often the case with this game.

C. Multiplayer Aspects

As shown in Fig. 5(a), the users did not greatly enjoy the feedback from the system but still deemed it enough to compare between users and develop a competitive aspect to the game. Participant P21, a male aged 39, stated simply

> "Beating other people is the only reason I play games."

D. System Design

Fig. 5(b) shows the user perception on mobility of the system, deemed very mobile. However, the perception of the sensing device itself saw some negative feedback. In particular, certain types of shoes did not lend themselves to attaching the sensor properly. Further, as participant P14 indicated

> "It would not work barefoot,"

such a system requires a certain type of clothing as is currently implemented. Fig. 5(c) shows that this irritated a few users. As a result, future generations of games should consider even less invasive sensing technology.

E. Future Developments

While this study has presented the development of a truly virtual sports environment game with pervasive sensing, it opens the door to significantly more work. A more complex game can be designed, that can last longer and present more information to the user through graphical means, be it health information or graphics to better immerse the user in the activities. Competitive aspects to such a game can be expanded upon, as can the multiplayer aspects and feedback. Furthermore, these movements can take further advantage of the mobility and open environment by increasing the range of movements and the sensors embedded and incorporated. As a larger user base adopts such a game, further questions on the classification algorithm itself must be addressed. These include questions regarding the modeling of large multiclass problems, skill levels, and better ways of combining data from various sensors. Once these goals are achieved, longer studies must be conducted, as is suggested by [5], for long-term adoption clinical benefits.

VI. CONCLUSION

This paper has introduced a unique development approach to truly mobile exergames with near-realistic activity recognition.

This study presents a merger of ideas to present a framework for a truly mobile, ubiquitous, and pervasive gaming platform using wearable sensors to monitor human activity. By first creating a recognition system for realistic soccer actions, as well as developing a game to map to these actions to create a realistic virtual environment, an intense and enjoyable gaming experience was created. Finally, ExerSurvey was employed in order to present a unified validation approach to effectiveness of the exergame. The survey, as well as the activity data presented in this study will be made available for future use in order to enable an acceleration of research in mobile active exergaming applications based upon realistic sports environments and other similar ideas to help further gaming and healthy exercise, as well as address potentially devastating epidemics such as childhood obesity.

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