Cypress: A Cyber-Physical Recommender System to Discover SmartPhone Exergame Enjoyment

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ABSTRACT
Many young adults do not exercise enough, choosing instead to spend time on electronic media (smartphone, Internet). Exergames, which gamify physical activity, can be effective at increasing physical activity in an enjoyable way. However, exergame discovery is still manual, ad hoc and challenging. Our objective is to research and develop *Cypress*, a cyber-physical recommender system that 1) uses smart-phone sensing to actively monitor user enjoyment of exergames played 2) learns the types of games liked and 3) recommends similar games when users become bored, thus keeping users engaged and exercising.

Keywords
Exergame, physical activity, recommender systems, smartphone, mobile sensing, machine learning.

1. INTRODUCTION
Physical inactivity increases the risk of many ailments including diabetes, cardiovascular disease, metabolic syndrome and some cancers and is one of the leading causes of death in the United States [1]. Obesity is the leading, preventable cause of health problems afflicting children and young adults, many of whom do not meet current guidelines of performing at least 60 minutes of moderate to vigorous physical activity daily [18]. Instead, many young people have sedentary, “online” lifestyles.

The prevalence of inactivity is partly because, other than organized sports, there are not many enjoyable physical activity alternatives for young people. Pervasive games, which extend the gaming experience into the physical realm (e.g., on city streets) could present viable exercise alternatives to engage young people since they are typically early adopters of technology. An *exergame* is a type of pervasive game that incorporates gameplay elements into exercise to increase physical activity in an enjoyable way.

Playing exergames have been shown to promote good health, increase aerobic fitness and improve metabolic and physiological variables including heart, oxygen and respiratory rates in young people [7]. The energy expended (about 546 kcal/hour) while exergaming is comparable to the energy expended while bicycling and swimming [6] and is adequate to serve as regular exercise [5].

If exergames are to be effective, sustained user engagement is key but presents a challenging research problem. 95% of all new game players stop playing within 3 months, and 85% of new players stop after one day [2]. While these statistics encompass all games, the numbers for exergames (a sub-genre) is likely to be similar, or worse. We assert that: 1) gamers typically stop playing as games lose their initial appeal and they become bored; and 2) connecting users to new games they will like when they lose interest in their current game is necessary, but challenging**.**

People play exergames mainly because they are fun, not because they promote physical activity [10]. However, exergame preferences vary depending on personality type, prior game experiences and gender [9]. For instance, Agu *et al. f*ound that while female gamers loved dancing games such as *Dance Dance Revolution*, male gamers hated them [9]. Many different exergame genres exist including sports, adventure and dance games, creating challenges in connecting youth to exergames of interest. Specifically: a) game search involves trial-and-error; b) game recommendations are driven by mass popularity not specific personal tastes; c) users have to actively seek new exergames d) measures of user enjoyment are not specific to exergames; and e) feedback on user enjoyment of exergames is currently limited mostly to sparse user reviews on websites such as Amazon.com. .

We envision a *Cyber-Physical Recommender System* (Cypress) that:

1) Monitors user enjoyment of exergames played using measurable, implicit indicators of interest to detect when a user is losing interest in his/her current game. These implicit interest indicators (e.g., excited gameplay, gaming frequency) can be gathered with minimal user burden; 2) Infers and assigns a user-specific enjoyment score (an E-Score) to each exergame played; 3) Learns the types of exergames each user likes over time, generating a user-specific exergame profile; 4) Actively discovers other exergames that fit an exergamer’s profile; and 5) Recommends new exergames whenever a gamer becomes disinterested in their current game in order to sustain engagement in exergaming.

2. OVERVIEW OF CYPRESS
Our research agenda focuses on researching and developing the Cypress recommender system initially on smartphones. Smartphones are widely owned across all demographics, ages, and socio-economic groups, providing a potentially large impact for our approach. In addition, smartphones can dually be used for: a) an *exergaming platform*, and b) *enjoyment monitoring* by gathering implicit measures of game enjoyment, generating enjoyment scores, and providing personalized recommendations whenever user enjoyment wanes.

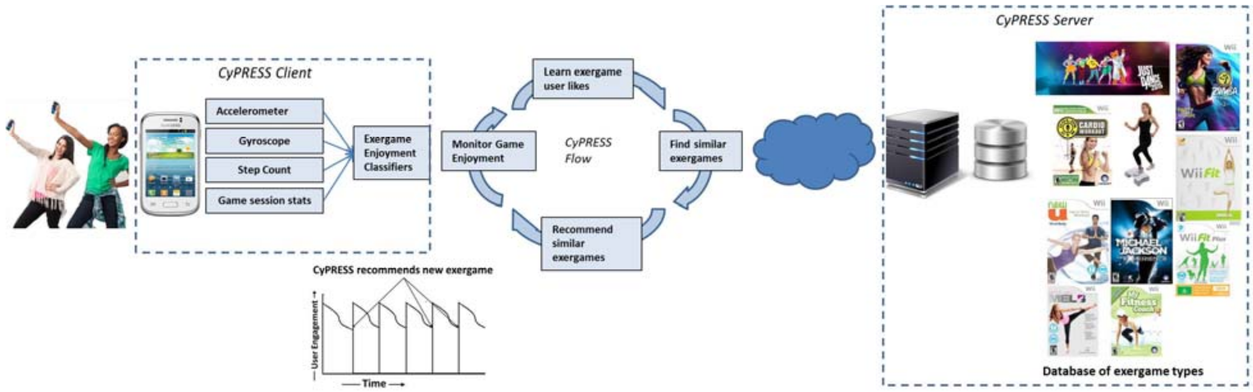

Figure 1: Cypress overview and usage scenario

Figure 1 illustrates an envisioned Cypress scenario. On the left, a user plays an exergame on her smartphone. The Cypress client, running on the phone, gathers implicit interest indicators using the phone's built-in sensors (e.g., accelerometer, gyroscope, and pedometer) as well as game session statistics (e.g., game duration and replay frequency). The implicit interest indicators are used as features to classify exergame enjoyment. Recommendations are triggered when a gamer searches for a suitable game or when Cypress detects that user enjoyment of the current game has dropped below a certain level. On the right, the Cypress server uses information on each user's enjoyment for each particular game to find and recommend new exergames. The profiles of the games (e.g., exploration game) are combined with user preferences (e.g., a preference for running games) and the opinions of other users to produce personalized game recommendations. The Cypress flow is depicted in the middle. Cypress detects each time the user's interest in the current exergame wanes (shown in the bottom graph) and finds and recommends new exergames based on user and game profiles. This enjoyment monitoring and new exergame recommendation cycle repeats, continuously maintaining user engagement and exercise.

Scenario Illustrating Cypress Usage

Lindsey is concerned about weight gain caused by her sedentary lifestyle. However, her previous efforts at exercising through sports have not been effective. Her friend Carol mentions Just Dance, an exergame that plays music, shows dance moves on the screen and grades her dance moves right on her smartphone. Lindsay tries Just Dance and loves it! For the next 3 weeks, she dances every day and loses 6 pounds. Lindsay is excited! Unfortunately, after three weeks, Lindsay knows all the dance moves and songs in the game, becomes bored and considers stopping playing altogether. ***The Cypress system detects her waning interest and recommends a new exergame, Zumba Fitness.*** *Lindsey tries the new game and also loves it. She becomes rejuvenated and continues to dance every day, losing 5 more pounds. Longer term, she continues to exercise, loses weight and improves her fitness.*

3. RELATED WORK

Prior work suggests that Cypress is indeed feasible:

1) Smartphone sensing of enjoyment: People-centric smartphone sensing [3], where data from a smartphone's sensors (such as an accelerometer, gyroscope or camera) are mined by intelligent algorithms to infer user behaviors and emotions, is particularly relevant to our work. For instance, Kuhn *et al.* [4] sensed with over 85% accuracy how much party attendees were enjoying the music by classifying how energized and synchronized to the music their dancing (sensed from a smartphone accelerometer) were. We propose classifying the accelerometer and gyroscope data to detect excited gameplay and indicators of engagement in an exergame.

2) Active discovery and recommendations of new exergames: Recommender systems have shown immense value and now account for 2/3rd of all Netflix movies watched, 35% of Amazon.com sales and increase Google News click-throughs over 1/3rd [13]. Recommender systems for health inform Cypress' development, particularly those that recommend exercise types and running routes, and give health advice. Wuttidittachotti et al. propose a mobile system that recommends exercises based on the user's health characteristics, but does not implicitly detect enjoyment nor focus on exergames [12].

3) Implicit measures of game enjoyment: Cypress learns user enjoyment patterns from measured smartphone sensor data. Game analytics [8], in which gameplay data is analyzed quantitatively in order to understand player behavior provides a foundation for synthesizing our exergame enjoyment measures. Prior work on methods and metrics to detect player disengagement [11] provide a starting point for statistics that might help determine engagement. Work on analyzing player session patterns to predict attrition is also useful for showing how game session data can be mined to ascertain player enjoyment.

4) Explicit measures of exercise and game enjoyment: Several questionnaires have been proposed to ascertain exercise and game enjoyment. The *Immersive Experience Questionnaire (IEQ)* [15] and *Game Experience Questionnaire (GEQ)* [14] are the most widely used game experience questionnaires. Questionnaires that measure user enjoyment of physical activity have been proposed, including the *Physical Activity Enjoyment Scale (PACES)* [16]. However, a questionnaire that combines exercise and game enjoyment is needed. We plan to synthesize one.

4. ENVISIONED RESEARCH APPROACH

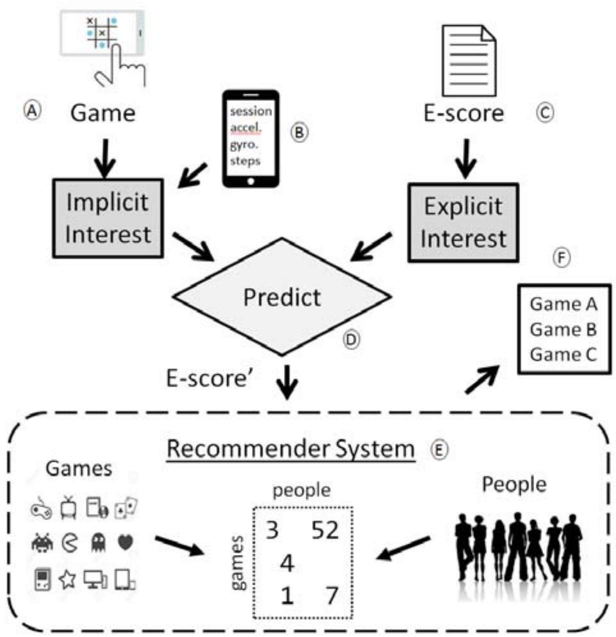

Figure 3: Our Proposed Phases of Research

In order to research and develop our Cypress exergame recommender system, phases of research (Steps A–F in Figure 3) need to be carried out:

Step A – Selection of exergames for experiments: Our experiments will gather data while users play selected exergames. Two current exergames from different genres (e.g., 1 dance and 1 treasure hunt exergame) will be selected for our pilot studies and preliminary analysis of smartphone sensor data that indicates exergame enjoyment. The exergames selected should be accessible to beginners and require reasonable amounts of exercise. Android will likely be the target mobile OS as it is widely available.

Step B – Smartphone instrumentation and generation of sensor data gathering app: One of our main research challenges is to convert the data captured by the phone into a reliable enjoyment indicator. The smartphone must be instrumented to gather sensor data (gyroscope, accelerometer, user steps, and game session events) from which implicit indicators of user interest in exergames will be synthesized. We will leverage *Funf*, MIT's open source sensor data gathering app, or Cornell's *Android Research Stack* to facilitate development of our data gathering app. Since Funf does not currently retrieve user step count and game launch/end events to generate session statistics, a custom app will be programmed to gather these data.

Step C – Adaptation of user game experience questionnaires: To gather ground truth data on user enjoyment of exergames, after playing each exergame, subjects in our studies will be surveyed about how much they enjoyed the exergame and its exercises. The user's response will be tallied to generate an *Enjoyment Score* (E-Score). Since no exergame-specific questionnaires exist, we will synthesize a new questionnaire to measure exergame enjoyment that will combine elements of previous game engagement questionnaires (e.g., the GEQ [14] and IEQ [15]) and exercise questionnaires (e.g., PACES [16]).

Step D – Synthesizing implicit interest indicators (gather smartphone sensor data, extract features, analyze): We will conduct a user study in which 30 exergamers (15 male, 15 female) will play 10 different exergames while we gather smartphone sensor data. Users will also talk aloud describing moments of enjoyment as they play, generating a transcript to assist in data analysis. After playing each game, users will complete our E-Score questionnaire to declare enjoyment levels. The smartphone sensor data will be extracted and analyzed statistically by looking for correlations (and regression analysis) between our E-Score and smartphone features (implicit interest indicators). The most correlated smartphone features will be used for classification of user E-Scores in a machine learning framework such as *Weka*. Different classifier types (e.g., SVM, naïve Bayes) will be compared. The best performing classifier will be used to generate a smartphone app that can classify a user's smartphone sensor data as s/he plays exergames to infer enjoyment levels.

Step E – Use predicted E-Scores to recommend new games: E-Scores inferred by our classifiers will be used to recommend new exergames. The Cypress recommender module will include profiles of exergames (e.g., game genre, exercise type) and players (e.g., age, gender, exercise preference). For each game/user combination, Cypress will keep the predicted E-Score, providing a large matrix, suitable for use by the recommender module. Game similarity, user similarity and predicted E-Score values for all played games will be used to recommend games in which a user may be interested. The recommender module will output a list of recommended games, and the strength of the predicted rating and links to the game.

Cypress will also continuously monitor when a user becomes disinterested in the exergame s/he is playing, increasing the risk of quitting exercising altogether. Increased inter-session times and decreased game session lengths have been found to be reliable predictors of attrition. When Cypress detects critically reduced user interest in an exergame, a new potentially interesting game will be suggested.

Cypress does not require any modifications to work on any exergames and should work with exergames on any app store. While exergame quality and quantity varies widely, those of interest to a user will emerge naturally in the recommender system as with other media (e.g., Movies).

5. RECOMMENDATION ENGINE

The Cypress recommendation engine will use *LensKit*, a Java-based recommender toolkit. LensKit provides an API for recommender system algorithms, with the ability to swap out different collaborative filtering algorithms. LensKit also includes an offline performance evaluation framework. Adaptation of recommender system technology employed in Cypress (via LensKit) will be required since challenges include: a) *early raters*, where recommendations cannot be provided for new exergames since no user ratings exist, or for new users where no prior history exists; b) *sparsity*, where the number of exergames in the Cypress database exceeds what most users can play, thus matrices containing the ratings of all items for all users are sparse, making predictions difficult; and c) *gray sheep*, where users with unique tastes do not benefit from the opinions of others because they do not consistently agree or disagree with anyone. Cypress will utilize content-based filtering to enhance the LensKit module [17]. While promising, this approach poses additional challenges including: effective taxonomies for exergames, determining game content characteristics from meta data (e.g., game descriptions), clustering content for content-based recommendations, and establishing usable user-profile settings.

6. CONCLUSION

Many young adults do not exercise enough, increasing health risks, instead choosing to spend time on electronic media (smartphone, Internet). Exergames, which gamify physical activity, have been shown to be effective at increasing physical activity in an enjoyable way. However, exergame discovery is still manual, ad hoc and challenging. Our objective is to research and develop Cypress, a cyber-physical recommender system that actively monitors user enjoyment of exergames played, learns the types of games s/he likes and recommends similar games when boredom is detected. Enjoyment will be inferred from user behaviors such as excited actions and game sessions, measured on the phone (accelerometer, gyroscope, step count and game session statistics). Ground truth will be obtained from a novel, exergame-specific enjoyment questionnaire providing an E-Score. Using machine learning, smartphone features are classified into user exergame enjoyment levels (predicted E-Scores). E-Scores and exergamer profiles are used to find exergames that fit each user's unique taste.

Many interventions result in an initial increase in physical activity but users typically return to baseline levels within a few months. Thus, longitudinal evaluation using a randomized controlled trial to test whether or not Cypress increases physical activity levels long-term (e.g., over 1 year) is planned as future work.

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