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User-optimized activity recognition for exergaming

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ABSTRACT

This paper presents SoccAR, a wearable exergame with fine-grain activity recognition; the exergame involves high-intensity movements as the basis for control. A multiple model approach was developed for a generalized, large, multiclass recognition algorithm, with an F Score of a leave-one-subject-out cross-validation greater than 0.9 using various features, models, and kernels to the underlying support vector machine (SVM). The exergaming environment provided an opportunity for user-specific optimization, where the expected movement can assist in better identifying a particular user's movements when incorrectly predicted; a single model SVM with a radial basis function kernel improved 12.5% with this user optimization.

1. Introduction

Exergaming, the use of exercise to control video games, or the incorporation of health information into video games, has been a growing field in combating a growing obesity epidemic. These games may address personal health [1], targeted therapies for rehabilitation [2], or exercise-levels of sports activities [3] captured by camera-based systems, such as the Microsoft Kinect [4]. One particular realm of exergames involves using body-worn sensors (e.g., accelerometers, gyroscopes, etc.) to allow users to control video games with body movements [5]. Such movements have been shown to generate moderate levels of physical activity [6,7]. While some systems use the mobile phone as the controller [8,9], more enhanced mobile games need to be developed to allow for a wider range of movements. Systems need to develop for enhanced recognition algorithms to identify those movements [3], monitor various levels of intensity need to be monitored [10], and adapt to multiple users while preventing cheating the exercise [11]. Indeed, exergaming can be a tool to combat sedentary behavior. Sedentary behavior, affects both adults [12] and children [13], leading to chronic conditions [14], that cause a financial burden on both individuals [15] and health care systems [16–18]. This work will investigate developing such an exergame's recognition algorithm.

Many activity recognition problems concern themselves with setting up a model and then showing this model is robust and general, either in a testing environment or in cross-validation [19]. However, it is possible to leverage specific information and context to improve classification results [20]. Indeed, often multiple models or hierarchical classifiers improve classification results, using structural information [19], conditional information [20], or expert knowledge to improve classification [21]. Once such a system is proven to be generally accurate, however, user-specific optimization can then become appropriate. Work in [22] introduces an incremental support vector machine, capable of retraining and optimizing as new data becomes available. [23] uses this method to update human recognition in video applications to

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improve accuracy. Further, [19,24] use contextual information and a method called active learning to update the models based upon contextual information. When to retrain, however, is an application-dependent problem.

This paper presents SoccAR, an Augmented Reality Soccer obstacle course exergame based upon the Temple Run platform to incorporate a dynamic mobility game with detailed sports-type, fine-grain actions, first presented in [25]. That work focused on the design of an exergame, a multiple model approach to classifying fine-grain activity in a large, multiclass recognition problem, and introduced a new mechanism for evaluating model effectiveness. This work will extend [25] by considering the multiple model approach designed and evaluating methods for optimizing the model performance, and extending them for user-optimization. By using the game engine as ground-truth generation for each movement, the system can retrain models for a specific user, helping improve the accuracy through increased usage. This work presents the retraining mechanism in both an online and offline setting and uses the prior work to introduce user-specific fine-grain activity recognition methods.

2. Related works

2.1. Sports exergames

Work in [2] presents a platform for developing an exergame to assist in stroke rehabilitation using accelerometers, representing a class of exergames with a specific goal and set of actions in mind. Work by [1] develops an entertainment-based exergame with multiplayer aspects to encourage competition. Similarly, work by [4] demonstrates a motion-based game for exercise and entertainment of adults, but uses a Microsoft Kinect that, while allowing freedom in a particular space, does not allow for a game that can be played anywhere and across any distance. Finally, a set of mobile games, such as those in [8,9], allows for gaming in any environment by using a mobile computing device (such as a smartphone) as the controller. So while these games allow for freedom in environment, they do not address a wide range of possible motions and exercises.

2.2. Fine-grain activity exergaming

Work in [3] describes the steps necessary to building an exergame that results in healthy and enjoyable gameplay with accurate motion classification. A tablet-based game is built from a list of soccer movements, which the paper defines as fine-grain, collected to develop an energetic and fast-paced game. A game-specific movement classification algorithm is created based upon a principal component analysis, hereafter known as Fine-Grain PCA. This algorithm classifies movements shown in the [7] to produce exercise-levels of intensity by guaranteeing a certain level of metabolic output. The classification algorithm presented in this work will result in a more accurate gameplay experience than that of Fine-Grain PCA, as will be shown in Section 6.

2.3. Multiple models works

Work in [26] builds hierarchical hidden Markov models in order to better identify activities of daily living by using multiple models. While improving accuracy of activities of daily living, particularly with similar movements, this structure is not set up for real-time processing. Work in [27] takes a multiple model approach to classifying patients with heart failure. The technique presented allows for a clustering of patients based upon contextual information (e.g. medical conditions and socioeconomic status). This work will similarly adapt this approach.

2.4. Incremental learning

Work in [28] presents a feature-reduction approach to finding an optimal point between algorithmic accuracy and game latency. While this heuristic approach can, potentially, find a user-optimal point, the base algorithmic accuracy cannot improve greatly as the model is never changed.

Work in [29] uses contextual information for co-training and retraining. All of these methods use context to create a subset of labeled data in order to reduce training time. This work builds upon these ideas, not necessarily concerned with reducing the training time, but using active selections of training data to improve the accuracy of a given system by analyzing the data in an on-line fashion and retraining any model when determined necessary.

3. Soccer exergame

This section describes the development of the SoccAR platform, initially presented in [25], which was a Temple Run-based obstacle course with soccer movements. A sensor platform inputted actions from the user in any environment and a computing device and display drove the game engine for the user to interact with, as shown in Fig. 1.

3.1. Head-worn display

Ultimately, what could make a game successful as a mobile game would be the ability to display to the user the gameplay environment while leaving the hands and legs free. To enable this, head-worn displays are needed. However,