Automatic Recognition of Protective Behaviour in Chronic Pain Rehabilitation

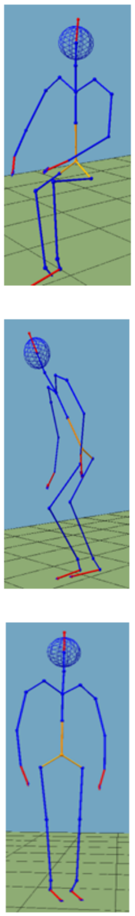

Fig.1. Example avatars generated using motion capture data of people with chronic pain: three frames from a sitting to standing exercise.

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Abstract
Exergames are increasingly being proposed for physical rehabilitation in chronic pain. They can be engaging, fun and can facilitate the setting of targets and evaluating performances through body movement tracking and multimodal feedback. While these attributes are important, it is also essential that psychological factors that lead to avoidance of physical activity are addressed in the game design. Anxiety about increased pain and/or of further damage often causes people to behave in a self-protective manner (e.g., guarding movement) and to avoid particular movements. Protective behaviour may itself cause increased pain or strain. In this paper we investigate the possibility to automatically detect such behavior. Automatic detection of protective behaviour can be used to adapt the exergame at run time to alleviate anxiety and increase treatment efficacy.

Author Keywords
Exergame; Automatic emotion recognition; Protective Behaviour; Machine Learning; Body movement.

ACM Classification Keywords
H.1.2. Human Information Processing.

PROCEDURE

Table 1. Data collection and automatic recognition procedure

Data [20]: 21 subjects with CLBP underwent 1-3 trials consisting of a range of physical exercises including sit-to-stand movements (fig. 1). Each trial lasted about 15 min. 4 experts labeled recorded videos to identify video segments with protective behaviour. Also, 105 instances of a sit-to-stand exercise were segmented from the motion capture and EMG data. A total of 47 sit-to-stand instances were labeled as *Guarding* as they had been identified by at least 3 experts as containing such behavior. The remaining 58 were labeled as *Not Guarding*.

Movement Features: Features were computed over each sit-to-stand data segment. The best recognition results were obtained by using: ranges of joint angles, means of joint energies [17] and means of rectified EMG values.

Automatic Recognition: An ensemble of 100 decision trees trained using a subset of all available features was created. Each tree was created using an in-bag sample of 2/3 of the original data.

General Terms

Algorithms; Human Factors.

Introduction

Rehabilitative therapy for chronic low back pain (CLBP) is effective so long as the subject adheres to the methods and uses them in everyday life [1]. However, adherence among people with chronic pain is often poor, partly due to the frustration and boredom of regular beneficial exercise and partly due to other psychological factors.

Exergames address some of these issues by bringing fun into exercise and to help people set targets, monitor performance and provide prompts [2, 3], but their effects tend to be weak in people with CLBP. One of most likely reasons of their limited success is that they do not take into account the psychological factors (e.g. anxiety) that lead to avoidance or caution about movements, which are wrongly believed to exacerbate pain or constitute physical risk [1, 4]. These psychological factors can undermine motivation to use exergames. If the exercises are performed despite anxiety, protective behavior can increase pain due to muscle over-contraction or failure to relax, thus wrongly confirming the fear that physical activity exacerbates pain. This problem is particularly prevalent when exercise is performed away from the guidance of a physiotherapist to provide feedback and reassurance.

Algorithms for affective state automatic detection (e.g., [5, 6, 15, 16, 21, 22]) could be used to feed back into adaptive game play to address psychological needs. In [7], for example, the shape and skills of the player’s in-game character are adapted to the player’s cognitive and physical capabilities according to the player’s stress level of the moment.

Similarly, in the context of CLBP, switching the control modality during game play from body movement to breathing patterns could, for example, prompt relaxation and increase confidence in beneficial exercises that would have otherwise been avoided. In addition, run-time encouragement, or multimedia feedback that provides a sense of control or of being monitored, could also be used for this purpose when necessary [8]. The amount of feedback during a movement and the amount of positive reinforcement on completion (e.g., [19]) can be based on the challenge of the movement and on previous avoidance patterns. However, feedback must be carefully used. Simple encouragement during an unchallenging exercise may be experienced as patronizing. Conversely, for more challenging exercises, it may bolster self-esteem [9]. Hence, switching the appropriate feedback mechanisms on and off at run-time as needed is crucial to help the person to progressively self-manage their condition [9].

To fulfill this need, the *Emo-Pain project* (www.emo-pain.ac.uk) is developing a multi-faceted virtual coaching system for CLBP rehabilitation [10, 11]. An important system requirement is the recognition of protective behaviours concomitant with fear of movement. Within the system’s framework there are two parallel recognition streams. The first is to interpret communicative levels of pain manifested as facial expressions and alterations in the voice [12, 23]. However, in this paper we focus on the second stream, the recognition of protective body movements due to anxiety or fear [13]. We acquired whole body motion data from people with CLBP (fig 1). Subjects executed

RESULTS

Table 2. Confusion matrix showing the number of out-of-bag predictions for an RF ensemble with 100 trees. G = *Guarding*, NG = *Not Guarding*. (columns: ground truth, rows: predicted outcome)

	G	**NG**
G	38 (81%)	9 (19%)
NG	12 (21%)	46 (79%)

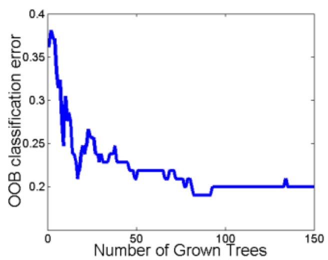

Fig 2. Out of bag classification error for an incremental number of grown trees, convergence occurs after 100 trees.

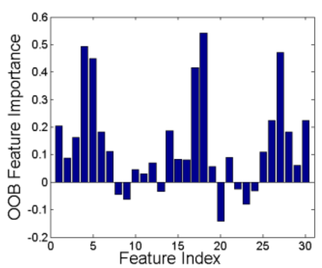

Fig. 3 Estimate of out of bag feature importance. Feature indices 1-13 for joint angle ranges, 14-26 for means of joint energy and 27-30 for the means of rectified EMG.

simple unconstrained movements while wearing a minimally invasive inertial sensor suit. We also recorded electromyography (EMG) data from the lumbar paraspinal muscles and the upper section of the trapezius muscles. Four experts (two physiotherapists and two behavioral psychologists) annotated the onset and offset timings of a set of predefined protective behaviours [20]. For data collection details see Table 1.

Recognition Method and Results

The use of machine learning methodologies for affective state recognition from body movements is a growing but underexplored area [14]. A major challenge is the high degree of complexity and variability inherent to unconstrained naturalistic whole body movements [15, 16]. The determination of features informative for learning systems is not only dependent on the affective state of interest but also on the type of action being conducted. Consequently for this study we investigate a specific sub-problem by considering one particular protective behaviour: *Guarding* [4] within motion segments of a single action type: *sit to stand* (fig. 1); thereby creating a scenario specific recognition model. In principle further models can be trained for all other behaviour/action combinations.

In this study we made no prior assumptions on which body part contributes to the expression of guarding. However, in doing this, a high dimensional input space is created. To account for this, we use the Random Forest (RF) method [18] to classify the target label *Guarding*. It is well understood that RFs are suitable for a high number of input features. Moreover, they can return estimates of the contributory importance of each feature. This is a valuable output given that feature selection for this problem is not well understood.

The results obtained using RF as a classification method for *Guarding* in *sit-to-stand* actions are showed in Table 2 (overall out of bag F1-score for *Guarding*: 0.78) and in Figure 2. Figure 3 compares the importance of the features; hip and knee angle ranges (indexed 1-6), hip and knee energies (14-19) as well as EMG (27-30) can be seen as important. Upper body angle ranges such as shoulders, elbow and neck (7-13) and their corresponding energies (20-26) return relatively low importance scores. Further analysis of the relevance of EMG vs. body form and kinematic features would be of interest to understand transferability of the approach to a simpler sensing setup (e.g., Microsoft Kinect).

Conclusions

Exergames are a new way for physical rehabilitation to introduce fun into an activity that is generally not pleasurable. However, we argue that these games should consider not only fun and performance but also target the psychological factors that constrain progress in rehabilitation by avoiding beneficial movements. By adding recognition capabilities for emotion and protective behavior into these systems, we enable game designers to adapt the game at run-time to maintain confidence and positive expectations of exercise. We present initial results in this direction.

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