

Automatic Recognition of Fear-Avoidance Behavior in Chronic Pain Physical Rehabilitation

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ABSTRACT

Physical activity is beneficial in chronic pain rehabilitation. However, due to psychological anxieties about pain and the perceived risk of injury, physical activity is often avoided by people with chronic pain. This avoidance is expressed through self protective body movement aimed at avoiding strain, particularly in painful areas. The detection of protective behaviour is crucial for effective rehabilitation advice and to enable a more normal lifestyle. Current technology to motivate physical activity in rehabilitation contexts does not address these psychological barriers. In this paper, we investigate the automatic recognition of a specific form of protective behaviour, *guarding*, common in people with chronic lower back pain. We trained ensembles of decision trees, *Random Forests*, on posture and velocity based features from motion capture and electromyographic data. Results show overall out of bag F1-classification scores of 0.81 and 0.73 for sitting to standing and one leg stand exercises respectively.

Categories and Subject Descriptors

H.1.2. Human Information Processing

General Terms

Algorithms, Experimentation, Human Factors.

Keywords

Emotion, Protective Behaviour, Machine Learning, Motion Capture, Electromyography, Body Movement, Pain Rehabilitation Technology, Physical Rehabilitation.

1. INTRODUCTION

Chronic (persistent) pain (CP) is a global health concern with an estimated one in ten adults affected [1]. It is defined as pain that persists past healing after injury or with no identified lesion or pathology [2]. Acute pain usually resolves as injury heals but CP can continue indefinitely through central nervous system changes. In acute pain, the signal warns of imminent or actual injury. However in CP, changes in the central and peripheral nervous system amplify pain signals and inhibition is reduced [3, 4]. The

same effects on pain experience are produced by negative mood, including anxiety, making it a major barrier to effective pain management.

Chronic condition self-management methods all have moderating factors that affect adoption and adherence [5]. But CP differs in that pain uniquely conveys threat [6] and generates fear and catastrophic thinking undermining adherence to activity programmes. Yet keeping active protects against weakening and stiffness; inhibits the neurophysiological mechanisms underlying spread of pain; increases confidence in physical capacity and underpins achieving valued goals [7] and improved quality of life [8]. Physiotherapists and other healthcare staff regularly educate and advise on activity as well as providing psychological support. However, limited human resource means there is an increasing emphasis on independent self-management, but this lacks psychological support and risks limited gains [9].

Although technology to support self-management and motivate physical activity has shown encouraging results for chronic diseases [10], it falls short of addressing the psychological issues such as fear, avoidance of and low confidence in movement. To this end, this study investigates the development of an automatic recognition system to detect expressions of psychological states by monitoring behavior. Behavioral studies in CP show that people consciously and unconsciously convey fear and anxiety through nonverbal behavior [11] which can be categorized as communicative behaviour, mainly facial expression, and protective behavior, such as guarded body motion [12]. Protective behavior can also have a communicative role.

Such behavior has detrimental effects on physical condition and capabilities but additionally communicative and protective behaviors impacts the person socially as they trigger negative perceptions by others [13][14]. Furthermore, studies in neuroscience and psychology show that postural and body movements that are typically expressed during a particular emotional or mental state can bias the person towards that mental state even when the posture or body movement is enacted for other reasons [15, 16, 17]. Technology capable of detecting such behavior could be used not only to facilitate physical therapy but also to increase awareness of posture and movement and offer strategies to change unhelpful habits. In Singh et al. [18], the authors discuss how physiotherapists make use of such cues to decide on the timeliness, amount and type of support to provide. This can vary from simple breathing prompts to partitioning the exercise to facilitate graded exposure, or simply providing information reassurance, encouraging feedback, praise etc.

There have been successful implementations in the recognition of

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facial pain expression [19, 20, 21, 22]. But to the best of our knowledge, pain-related expressions from body movement have barely been studied although, in the wider context of generic affective states, there has been much recent work on recognition from body movements and postures (for a review see [23]). In particular Kleinsmith et al. [24] and Savva et al. [25] have shown that this is possible in full-body sports game contexts and during pauses between physical exercises. Also, in [24, 26] the authors investigate the possibility to categorize affective behavior along affective dimension of valence, arousal, action tendency and dominance. In this paper, we investigate the automatic recognition of a specific form of protective behaviour, *guarding* [11] which is common in people with chronic musculoskeletal pain.

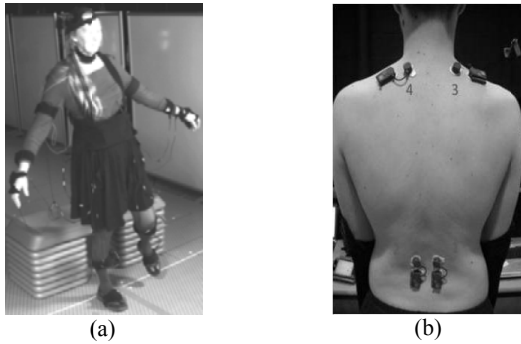


Figure 1. Sensor attachments (a) subject with Velcro strapped inertial sensors undertaking a one leg stand exercise, (b) adhered locations of the four wireless sEMG probes.

2. METHOD

The use of machine learning methodologies for affective state recognition from body movements is a growing but underexplored area [23]. A major challenge is the high degree of complexity and variability inherent to unconstrained naturalistic whole body movements. 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 scenario by considering one particular type of protective behavior: *guarding* [11] which is defined as: *stiff, interrupted or rigid movement that cannot occur while motionless*. We model this behavior within motion segments of two exercise types that tend to generate anxiety in people with low-back chronic pain (CLBP): *sit to stand* (Fig. 1a) and *standing on one leg* (Fig. 1b); thereby creating scenario specific recognition models. In principle further models can be trained for all other behaviour/action combinations. This is to specify the context and to reduce the complexity of the modeling; also we focus on CLBP as it is one of the most common forms of CP.

2.1 Data Collection

We used a multimodal dataset presented in [27] of people with CLBP doing physical exercise. The subjects wore an adapted Inertial Measuring Unit (IMU) based motion capture system (Animzaoo IGS-190). Each sensor was attached in parallel with a minimal number of Velcro strapping on each body segment (Fig 1a). This was done to minimize discomfort and invasiveness foregoing the standard method of wearing tight fitting overall suits with embedded sensors. This system was calibrated by way of re-setting the generated avatar to an assumed standing posture after asking the subject to stand in the same posture. Each gyrosopic sensor returned 3D Euler angle triplets in the

BioVision Hierarchy format (BVH) at a sample rate of 60Hz. In conjunction with skeletal proportions annotated from still photographs of each subject, the 3D Cartesian positional triplets of 26 anatomical nodes over the whole body were calculated using Matlab motion capture toolbox [28]. In addition, 4 wireless electromyographic (EMG) sensors (BTS FREE EMG) were attached to the lumbar paraspinal muscles and the upper section of the trapezius muscles (Fig. 1b) due to the focus on low back chronic pain. Each pair of sensors was placed laterally equidistant to the spine. Skin was cleaned using alcohol before the probes were adhered to reduce noise and artifacts caused by impurities on the contact area. The recording procedure of the two sensing systems was automatically triggered for synchronization [29].

Four experts (two physiotherapists and two behavioral psychologists) annotated the onset and offset timings of *guarding*. The experts read and understood the definition of the label and visually inspecting full scenario videos of each trial with the use of full playback controls post recording. In this study we focus on binary decisions between *guarding* and *not guarding* rather than graded levels of *guarding* which would introduce a further subjective dimension. The level of *guarding* is also undefined in the clinical domain. Moreover, binary categorizations provides sufficient information since many therapeutic interventions are reliant on the presence of *guarding* rather than its extent [18].

Twenty one subjects with CLBP underwent 1-3 trials consisting of a range of common physical exercises which place demands on the lower back; these include between 3-5 repeated sitting to standing ('sit-to-stand') and between 3-6 episodes of standing on one leg ('one-leg-stand'). Overall we consolidated 105 separate instances of 'sit-to-stand' and 152 instances of 'one-leg stand' and were used in this analysis. A total of 47 'sit-to-stand' instances were labeled as *guarded* as they had been identified by at least 3 experts. The remaining 58 instances were labeled as *not guarded*. For the episodes of 'one-leg-stand', 69 instances were labeled as *guarded* and 83 *not guarded*. However, due to a high degree of sparsity in the number of labels for 'one-leg-stand' the minimum number of experts needed to identify *guarded* was reduced to 2 [27].

2.2 Feature extraction & modeling

Three feature categories were calculated to account for posture based spatial information; velocity based dynamic information and back muscle activity levels. The full body postural information is described by the inner angles in 3D space at 13 joint articulations; the velocity based information which we will refer to as 'energy' is calculated from the square of the angular velocities at each of the 13 joints [30]. Finally, for the muscle activity levels the value of the upper envelope of the rectified signal is taken from each of the 4 EMG sensors.

We treat this problem as a classification problem based on a static feature vector which can be calculated over the whole instance of an exercise. Initial experiments showed the use of the ranges (maximum value minus the minimum value) of the joint angles, mean values of joint energies and mean values of rectified EMG values delivered optimal results. This results in a 30 element feature vector (13+13+4).

Due to the lack of precedent for this type of class label, we make no prior assumptions as to 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 [31] to classify the target label. It is well understood that RFs are suitable for a high dimensional data space. Moreover, estimates of the contributory importance of each

feature can be done by the permutation of feature values within out-of-bag (OOB) instances followed by the calculation of the difference in classification error caused. This is a valuable indicator given that feature selection for this problem is not well understood.

3. RESULTS

Initial experiments in varying the number of trees for each ensemble showed that using 150 trees each grown using a subset of features was optimal for the ‘sit-to-stand’ instances and an ensemble of 50 trees for the ‘one-leg-stand’ data. Each tree was created using an in-bag sample of 2/3 of the original data for both exercises. The results obtained for *guarding* for both types of exercise are showed in Table 1. The overall out of bag F1-score to classify *guarding* for ‘sit-to-stand’ was 0.8. The results for ‘one-leg-stand’ show similar performance though slightly lower with an overall F1-score of 0.73. Figures 2a and 2b show the OOB classification error for the two exercises respectively.

Table 1. Confusion matrices showing the number of out-of-bag predictions using Random Forest.

Ground Truth	Predicted for Sit to Stand	
	Guarding	Not-Guarding
Sit-to-Stand	Guarding	38 (81%)
	Not Guarding	9 (19%)
One-Leg-Stand	Guarding	12 (21%)
	Not Guarding	46 (79%)

Ground Truth	Predicted for One Leg Stand	
	Guarding	Not-Guarding
One-Leg-Stand	Guarding	42 (61%)
	Not Guarding	27 (39%)
One-Leg-Stand	Guarding	8 (9%)
	Not Guarding	75 (91%)

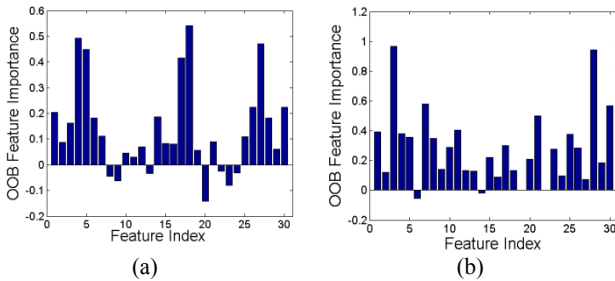


Figure 2. Feature importance histogram for ‘sit to stand’ (a) and ‘one leg stand’ (b).

The relative importance of the features was analysed to understand their role in the classification process. Figure 2a compares the importance of the features for the sit-to-stand exercise in which five groupings of features emerge. Hip and knee angle ranges (indexed 1-6), hip and knee energies (indexed: 14-19) as well as EMG (indexed: 27-30) can be seen as important. Upper body angles ranges such as shoulders, elbow and neck (indexed: 7-13) and their corresponding energies (indexed: 20-26) return relatively low importance scores. This suggests divergence of importance that is dependent on anatomical location, with the lower body as key.

Figure 2b also shows high relative importance to lower leg angles (indexed 1-6) and EMG levels of the left side of muscles (indexed 28 and 30). Energy values are not returned as important in comparison to Figure 2a (indexed 14-26). This indicates velocity based information is slightly less discriminative for the one leg

stand exercise as it is for the sit to stand exercise. This suggests a divergence in importance that is dependent on whether the feature is a static posture or a speed descriptor.

4. CONCLUSIONS

These initial results are promising for both physical exercises (F1-score: 0.8 and 0.73) and shows that supervised machine learning on labels with a high level of abstraction such as *guarding* is feasible if a scenario specific approach is used. However, it must be noted that the scores are based on OOB validation which is not strictly robust to unseen users. Therefore the applicability of this model would be limited to person specific systems which can be tailored one user. In order to be applicable to any user contexts further studies must be done with leave one subject out validation schemes. The RF algorithm was chosen as it has shown interesting performance in the machine learning literature as well as for its capacity to evaluate relative feature importance. This latter analysis is very important as it helps to understand the level of feature granularity that a sensing system would require.

The differences in feature importance for the two exercise types show the sensitivity of such systems to the context of the movement. For sit to stand, the system highlighted the importance of lower body parts and for one leg stands postural descriptors were important. In contrast, the expert observers rated the videos with a more holistic perspective, with overall velocity being intuitively important for *guarding* given its definition. However, it should be noted that unlike the system the observers were not privy to the EMG information and they applied their ratings on a per trial/subject basis whereas the system learned on a mixed randomized sample sets.

This understanding is timely since less obtrusive low cost motion capture systems are becoming more viable. For example in the Kinect system the number of anatomical nodes generated and capture rate is already sufficient and tracking accuracy is improving. Also, new Arduino-based Electromyograms are making muscle activity measurement more affordable for home-based rehabilitation and open the possibility to create muscle measuring devices that are easy to wear (e.g., an EMG-belt). Hence it is important to understand the minimal configurations for such systems.

For CP rehabilitation the robust recognition of *guarding* can pave way to adaptive feedback in the user interface [32]. Control modality during an exercise game could be switched from body movement to breathing patterns once guarding behavior is detected. This could prompt relaxation and increase confidence in otherwise avoided exercises. In other contexts, such adaptations have increased positive experiences. In [33], the shape and skills of the player’s in-game character are adapted according to the player’s real time stress level. Finally, run-time encouragement, or multimedia feedback that provides a sense of control could also be used. The amount of positive feedback during or after a movement (e.g., [16]) can be based on the extent of the movement difficulty and on previous avoidance patterns. However, psychology based feedback must be appropriately designed. Simple encouragement during unchallenging exercises may be perceived as patronizing, while for more challenging exercises it may bolster self-esteem [18].

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