Prediction of symptom duration and pain intensity from patellofemoral pain maps using deep learning

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Abstract

Introduction: Patellofemoral pain syndrome (PFPS) is a musculoskeletal condition that presents as pain behind or around the patella without known structural changes [1]. Partial correlations between perceived size of PFP from pain maps and symptom duration along with pain intensity has been indicated in previous studies [2], however morphology and location of PFP remains unexplored. Based on deep learnings objects detection capabilities, convolution methods can be used to detect image-features related to morphology. The aim of this study is to determine the performance of deep learning classification according to symptom duration and pain intensity, based on morphology and location of perceived PFP from pain maps.
Methods and materials: PFP drawings were collected on lower extremities body-schema and encoded into three different data representations in respect to morphology and location and a combination of the two. The distribution of the outputs were analyzed and used for defining the classification intervals for symptom duration (<12 and >36 months) and pain intensity (<4 and >8 on VAS). Estimation of generalization performance of the models was calculated through 5-fold cross validation during the training. Type 1 and type 2 errors were computed and results were compared between the three input representations.
Results: The results showed that the combined representation performed with the highest accuracy (67%). The location representation and morphology representation scored 63% and 62%, respectively, based on pain intensity. Generalization during training showed a higher accuracy for pain intensity classification (highest acc: 67% SD: 6.78) than symptom duration (highest acc: 57.85% SD: 4.95) using combined data representation. (TEST RESULT MISSING: will come later)
Discussion: Despite pain intensity being defined as multidimensional and subjective, the performance accuracy were higher than that of symptom duration. The results may indicate that a combination of the morphology and the location of the pain influence the classification performance in relation to symptom duration or pain intensity. Currently, it is unclear if deep learning methods may be a suitable approach for classifying PFPS to work as support in a clinical setting, to which further investigation is necessary. Improvements could be found when more data become available to better reflect generalization patterns in PFP drawings.

I. Introduction

Patellofemoral pain syndrome (PFPS) is a painful musculoskeletal condition that is presented as pain behind or around the patella [1, 2]. PFPS affects 6-7 % of adolescents, of whom two thirds are highly physically active [3]. Additionally the prevalence is more than twice as high for females than males [3, 4]. PFPS may be present over a longer period of time where a high number of individuals experience a recurrent or chronic pain [5] and may also lead to osteoarthritis [4, 6].
Patellofemoral pain (PFP) is often described as diffuse knee pain, that can be hard for individuals to explain and localize [5]. Despite the fact that individuals feel pain in the knee, there is no structural changes in the knee such as significant chondral damage or increased Q-angle. Because of this there is no definitive clinical test to diagnose PFPS and it is thereby often diagnosed based on exclusion criterias [4] to which PFPS is also described as an orthopaedic enigma, and is one of the most challenging pathologies to manage [7]. To assist diagnosis of PFPS, pain maps may be used as a helpful tool for the individuals to communicate their pain by drawing pain areas on a body outline [8].

A study by Boudreau et al. indicates through the use of pain maps that it is possible to find a correlation between the size of the pain and the symptom duration as well as pain intensity for individuals with

PFP longer than five years.[9] However, it is unknown whether the morphology and locations of the pain have an influence on the symptom duration and pain intensity. It is assumed that relation between pain maps and symptom duration or pain intensity is non-linear, because the perceived PFP is subjective and is considered as multidimensional [**?**]. To investigate the nonlinear relation, deep learning is used, which is a method that has not been found used in this context before.
The goals of this project is to explore how accurate a deep learning model can classify pain maps according to symptom duration and pain intensity by using a limited dataset. The pain maps are encoded into multiple data representations to investigate whether morphology and location have an influence on symptom duration or pain intensity. Because of the imbalance in prevalence between females and males, the gender is included as a feature in the deep learning model.

The aim of this study is to explore classification performance of a deep learning model, using PFP pain maps and gender as input to classify either symptom duration or pain intensity.

It is hypothesized that a deep learning model that uses pain maps and gender as input parameter has a higher performance when classifying according to symptom duration than pain intensity.

The secondary aim is to investigate if multiple pain map representations, which reflect the morphology and location of the pain, affect the deep learning model classification performance.

It is hypothesized that different data representations of pain maps, reflecting morphology and location of pain, affect the performance accuracy of a deep learning model when classifying according to symptom duration or pain intensity.

II. Methods

Data and manual data handling

Data used in this study were collected beforehand from an on-going clinical trial (FOXH) which is conducted in collaboration with Danish and Australian universities. The data consists of pain maps which were drawn by individuals with PFPS through the use of an application, Navigate Pain, in a clinical setting. The pain maps are both from individuals with uni- and bilateral PFP, an example of these are shown in fig. 1.

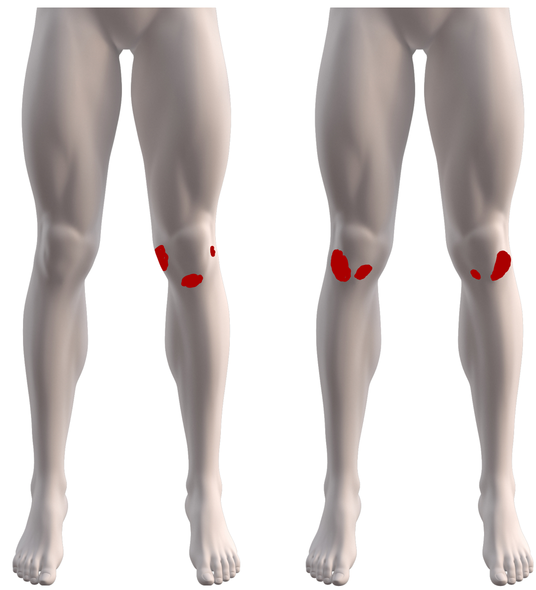

Fig. 1: *Pain maps from individuals with uni- and bilateral PFP. The red markings indicate the area of pain perceived by the individuals.*

In addition to the pain maps related information regarding the individuals was available. Before using the data in the deep learning models, a manual data handling was necessary to match the given pain maps and associated ID on the individuals, which resulted in 217 available pain maps. Furthermore, specific information like gender, symptom duration and pain intensity were collected from the appurtenant information. The number of pain maps with associated gender and symptom duration, was 205. Additionally, there were 197 pain maps with associated gender and pain intensity.

Software application: Navigate Pain

Navigate Pain is a software application that is used to visualise the location, morphology and spatial distribution of pain from individuals to healthcare personnel. The application permits individuals to draw their pain with different colors and line thickness onto a body outline. Navigate Pain android was developed at Aalborg University and a commercial web application is available at Aglance Solutions (Denmark).[12]

Knee regions

To define the location of the PFP the knees are divided into 20 regions, which are inspired by Photographic Knee Pain Map (PKPM). The divisions are designed to categorise location of knee pain for diagnostic and research purposes. PKPM represent both knees that makes it possible to identify unilateral and bilateral pain.[13] The knee regions are illustrated in fig. 2.

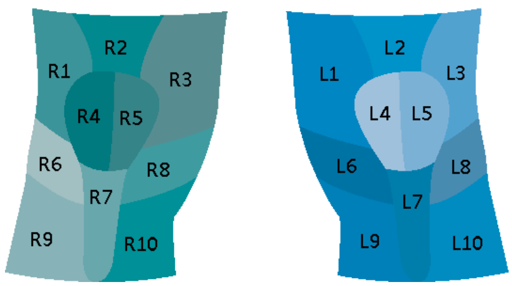

Fig. 2: *The regions of the left (L1-L10) and right (R1-R10) knees, where each knee is split into ten regions.*

The regions are based on the anatomical structures according to the areas where individuals often indicate pain. There are ten regions on each knee, where region 1 and 3 represent the superior lateral and superior medial areas for patella. Region 2 refers to quadriceps tendon. The patella is divided into lateral and medial regions, which are region 4 and 5. Region 6 and 8 are lateral and medial joint line areas. Patella tendor is region 7 and the two last regions, 9 and 10, are tibia lateral and medial.[13]

Data representations

To investigate whether morphology and location of pain have an influence on the outputs, symptom duration and pain intensity, the pain maps are encoded in multiple data representations. The pain maps were processed in MatLab, where the images were resized, since they were collected at different resolutions (screen sizes) and cropped to sort out unnecessary data like the areas inferior and superior to the knee. Each data representation is reflected in a matrix consisting of the pain maps, gender and the output, symptom duration and pain intensity. Since the original pain maps reflecting the morphology of the pain, thus the morphology-representation does not require further manipulation.

To investigate whether the location alone have a correlation to the outputs, a simplified representation of the pain maps are created. The location of the pain is then reflected by the use of the defined knee regions (fig. 2), where each region represent a value of 0 (not active) or 1 (active) in a vector. The values were defined by using a threshold to determine whether a region was considered active in relation the amount of pain. A threshold was required to increase the confidence of an active pain region by avoiding minimal contributions e.g. small pain areas in the associated regions. Simultaneously the threshold should not be too large so that pain areas was excluded. The threshold was decided based on an analysis on five random pain maps, where threshold values of 0, 5, 10 and 15% was compared. The threshold represent which minimal percentage of pain should be present in a specific region before it is considered active. Based on the analysis a 5% threshold was chosen.

Lastly, a data representation which reflects a combination of morphology and location of the pain, is prepared to explore if the interaction of morphology and location of pain would give a better classification according to the outputs.

Linear regressions

It was assumed that the data was nonlinear, because PFP is subjective and multidimensional. To verify this assumption of nonlinearity, linear regression on simple features was investigated. These features respond to number of pain pixels and number of active pain regions in relation to symptom duration and pain intensity. If it was possible to find a linear correlation between these simple features and the outputs, it may not be significant to investigate the morphology and the location of pain in deep learning models. Four linear regressions were explored, which resulted in R^2 values shown in tab. 1.

Feature combination	R^2
Pain pixels & symptom duration	0.0460
Pain pixels & pain intensity	0.0117
Active regions & symptom duration	0.0357
Active regions & pain intensity	0.0083

Table 1: *Feature combinations and associated R^2 values.*

Based on the four linear regression models, it was assumed that single features, number of pain pixels or number of active pain regions, do not have a linear correlation with the outputs, symptom duration or pain intensity. Hence a deep learning model may find patterns in the pain maps in relation to either symptom duration or pain intensity.

DEEP LEARNING

III. Results

resultttt

IV. Discussion

Discussss

V. Conclusion

conclusionnnnn

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