Prediction of pain duration and 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 pain duration along with 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 pain duration and 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 pain duration (<12 and >36 months) and pain intensity (<4 and >8 on VAS). Estimation of generalization performance of the models was calculated through 10-fold cross validation during the training.*
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 pain duration (highest acc: 57.85% SD: 4.95) using combined data representation.*
Discussion: *Despite pain intensity being defined as multidimensional and subjective, the performance accuracy were higher than that of pain duration. The results may indicate that a combination of the morphology and the location of the pain influence the classification performance in relation to pain duration or intensity. Currently, it is unclear if deep learning methods may be a suitable approach for classifying PFPS to work as support in clinical settings, 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]. Chronic pain may be maintained by the phenomenon central sensitization, which may result in increased areas of pain over longer periods of time. Furthermore, PFPS may 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. Because PFP is not caused by structural changes, no definitive clinical test may be used to diagnose PFPS and 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 there is a correlation between the size of the pain and the pain duration as well as intensity for individuals with PFP longer than five years.[9]
However, it is unknown whether pain duration has an influence on morphology of the pain and location, as well as whether morphology of pain and location have an influence on pain intensity. It is assumed that relation between pain maps and pain duration or pain intensity is complex, because the perceived PFP is subjective, and considered as multidimensional [**?**]. Additionally the study by Boudreau et al. did not find a fully correlation between pain maps and pain duration or pain intensity for individuals with a pain duration below 5 years. To investigate the potential nonlinear correlation, a previously unused deep learning method is used.
The goals of this project is to explore how accurate a deep learning model can classify pain maps according to pain duration or pain intensity. It is assumed that pain duration is a better predictor than pain intensity, because the perceived pain is subjective, and may be affected by multidimensional factors. The pain maps are encoded into multiple data representations to investigate whether morphology and location are correlated to pain duration or intensity.
The data representations are encoded into three representations, which reflect either morphology of pain or location, and a combination of morphology and location of the pain. The data representations are refereed to as morphology-, location- and combined-representation. There may be a difference in how gender reports pain intensity, where females reports more intense and frequent pain. Furthermore, there is an imbalance in prevalence between females and males, thus gender is included as a feature in the deep learning model.

Aims

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

The secondary aim is to compare the performance accuracy of deep learning models with different pain map representations (morphology-, location- and combined-representation), when predicting pain duration or pain intensity.

It is hypothesized that a combined-representation will have a higher performance accuracy when classifying according to pain duration or pain intensity in a deep learning model, than morphology- and location-representations.

II. Methods

Pain maps 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 pain maps were drawn by individuals with PFPS through the use of an application, Navigate Pain, in a clinical setting.
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, an example is shown in fig. 1. Navigate Pain android was developed at Aalborg University.[10]

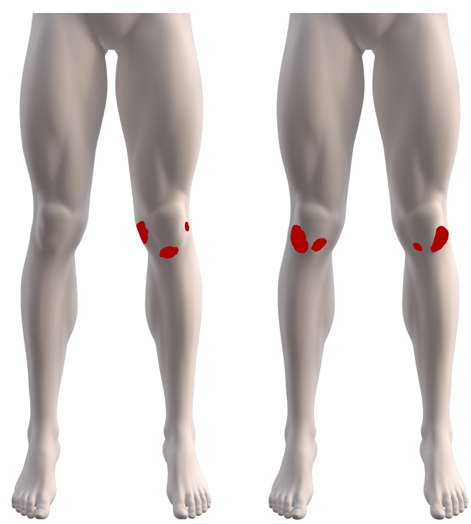


Fig. 1: *Pain maps from individuals with uni- and bilateral PFP. The red markings indicate the area of pain perceived by the individuals.*

The total number of pain maps available was 217, but only 205 pain maps with associated gender and pain duration, and 197 pain maps with associated gender and pain intensity was available.

Pain location

The knees are divided into regions based on the underlying anatomical structures, which may have a correlation to pain duration or pain intensity. The locations 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.[11] The knee regions are illustrated in fig. 2.

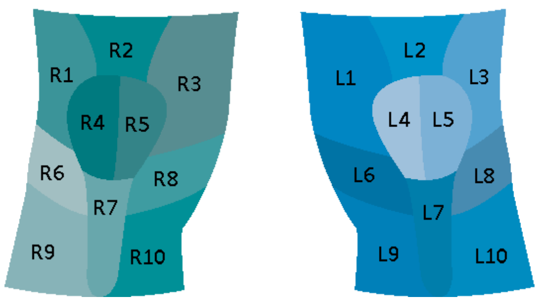


Fig. 2: *The regions of the left (L1-L10) and right (R1-R10) knees, where each knee is split into ten regions.*

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.[11]

Data representations

To investigate whether morphology and location of pain have an influence on the outputs, pain duration and 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, pain duration and intensity. Since the original pain maps reflecting the morphology of the pain, thus the morphology-representation does not require further manipulation.

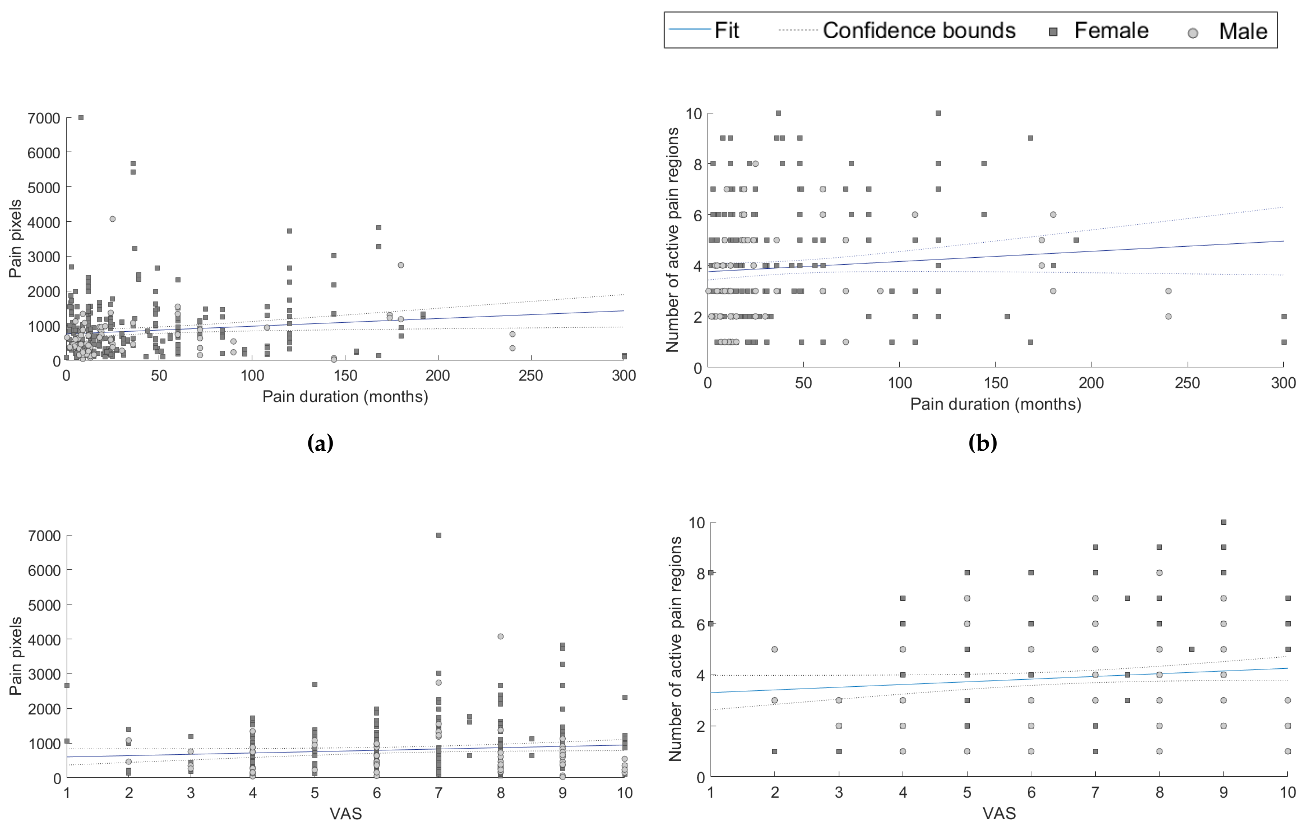
To investigate whether the location alone have a correlation to the outputs, a simplified representation of the pain maps are created. The location of the pain is then reflected by the use of the defined knee regions (fig. 2), where each region represent a value of 0 (not active) or 1 (active) in a vector. 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 reflecting the size of the pain was investigated. This decision was based on the phenomenon central sensitization that may result in widespread, to which this might be reflected in the number of pain pixels and active pain regions. Additionally, is a linear correlation according to the pain intensity investigated. The linear regression is shown in fig. 3.

Based on the four linear regression models, it was shown that single features, number of pain pixels or number of active pain regions, did not have a clear linear correlation with the outputs, pain duration or intensity. Hence a deep learning model may find patterns in the pain maps according morphology or lo-



(a) **(b)** **(c)** **(d)**

Fig. 3: *Linear correlations of pain pixels and pain duration (a), active pain regions and pain duration (b), pain pixels and pain intensity indicated in VAS (c), and active pain regions and pain intensity indicated in VAS (d).*

cation of pain in relation to either pain duration or intensity.

Deep learning models

Deep learning models were developed on a computer with 4x “Intel® Core^{TM} i7“ CPUs and one single GPU of type "Geforce GTX 970M", using the programming language Python v3.6.3. Libraries used was Keras with a TensorFlow backend.

Multiple deep learning models suitable to the three data representation were created. The models used supervised learning, which is defined as a network learning to classify a given input corresponding to a specific output [12]. The models classify the input, pain maps and gender, in relation to the determined outputs, pain duration or pain intensity.

Two of the models, which managed the morphology-, and the combined morphology and location-representations, were developed using the same

model architecture consisting of convolutional- followed by pooling layers and fully connected layers. Convolutional were used because it's highly classification in images that automatically learn a complex pattern by extracting visual features from the pixel-level content [13, 14]. The combination of convolutional and pooling layers performed feature extraction while the classification was made by fully connected layers.
The model that classified the location should not process morphology, thus a convolutional layer was not necessary, and thereby only contained fully connected layers.

Optimization of models
Optimization of the three model were done using a validation subset, whereto graphs plotting validation accuracy and loss were compared with training accuracy and loss. This was used to estimate the optimal number of epochs to reduce overfitting the model to the training subset. Further optimization were done using manual search on hyperparameters, from which improvements were based on an average accuracy, sensitivity and specificity gained from 10-fold cross validation.

III. Results

Results on generalization performance when using 10-fold cross validation, after final optimization for morphology-, region- and combined representation are shown in tab. 1. This is done for pain duration and pain intensity classifications to which an average accuracy, sensitivity, and specificity are calculated along with it's corresponding standard deviations.

IV. Discussion

Bullet points:

- results, compare them to regression
- accuracy, sensitivity and specificity
- Pain duration vs pain intensity
- Split body approach
- data amount (not large enough)

V. Conclusion

conclusionnnnn

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	Morphology representation		
	Avg. accuracy (%)	Avg. sensitivity (%)	Avg. specificity (%)
Pain duration	59.51% (±11.20%)	62.16% (±21.59%)	62.20% (±18.13%)
Pain intensity	65.04% (±10.83%)	48.23% (±0.28%)	71.02% (±0.12%)
	Region representation		
Pain duration	54.56% (±12.81%)	50.68% (±0.15%)	59.55% (±0.15%)
Pain intensity	63.33% (±1.67%)	0.00% (±0.00%)	63.33% (±0.02%)
	Morphology and region representation		
Pain duration	55.49% (±9.55%)	55.23% (±0.15%)	56.99% (±0.12%)
Pain intensity	65.14% (±12.87%)	37.50% (±0.35%)	67.34% (±0.15%)

Table 1: *Generalization performance of the three models, which use the morphology-, region- and morphology and region-representation.*