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A machine learning approach for the identification of kinematic biomarkers of chronic neck pain during single- and dual-task gait

David Jiménez-Grande [a], S. Farokh Atashzar [b,c], Valter Devecchi [a], Eduardo Martinez-Valdes [a], Deborah Falla [a,*]

[a] Centre of Precision Rehabilitation for Spinal Pain (CPR Spine), School of Sport, Exercise and Rehabilitation Sciences, University of Birmingham, UK
[b] Electrical & Computer Engineering, Mechanical & Aerospace Engineering, New York University (NYU), United States
[c] NYU WIRELESS and NYU CUSP, United States

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ABSTRACT

Background: Changes in gait characteristics have been reported in people with chronic neck pain (CNP).
Research question: Can we classify people with and without CNP by training machine learning models with Inertial Measurement Units (IMU)-based gait kinematic data?
Methods: Eighteen asymptomatic individuals and 21 participants with CNP were recruited for the study and performed two gait trajectories, (1) linear walking with their head straight (single-task) and (2) linear walking with continuous head-rotation (dual-task). Kinematic data were recorded from three IMU sensors attached to the forehead, upper thoracic spine (T1), and lower thoracic spine (T12). Temporal and spectral features were extracted to generate the dataset for both single- and dual-task gait. To evaluate the most significant features and simultaneously reduce the dataset size, the Neighbourhood Component Analysis (NCA) method was utilized. Three supervised models were applied, including K-Nearest Neighbour, Support Vector Machine, and Linear Discriminant Analysis to test the performance of the most important temporal and spectral features.
Results: The performance of all classifiers increased after the implementation of NCA. The best performance was achieved by NCA-Support Vector Machine with an accuracy of 86.85%, specificity of 83.30%, and sensitivity of 92.85% during the dual-task gait using only nine features.
Significance: The results present a data-driven approach and machine learning-based methods to identify test conditions and features from high-dimensional data obtained during gait for the classification of people with and without CNP.

1. Introduction

Neck pain has become a global public health issue affecting 70% of the population at some point in their life Goode, et al. [1]. The incidence of neck pain has increased over the last 25 years, and the number of people suffering from this condition will likely continue to increase [2].

A wide range of physical adaptations have been observed in people who present with chronic neck pain (CNP) including reduced range of neck motion, slower neck movement, altered variability of neck movements and changes in neck muscle activation when performing neck-specific tasks [3–6]. Additionally, people with CNP can display changes during more global tasks such as walking including a narrower step width, a shorter step length and a slower gait speed [7–12]. Kinematic differences between asymptomatic people and those with CNP during gait can become even more evident when performing more complex tasks such as walking whilst simultaneously rotation the head [8].

Performing a secondary task such as continuous head rotation while walking (i.e., dual-task gait) demands more cognitive attention and coordination as well as fine postural adjustments. This not only challenges motor control performance but also cortical processes as two different tasks are competing for the same cortical resources at the same time [13]. Earlier work has shown that people with CNP walk at a slower gait speed during dual-task gait [14] and that the variability of their trunk rotation reduces during this more complex gait condition [8]. Given that kinematic differences between people with and without CNP

* Correspondence to: Centre of Precision Rehabilitation for Spinal Pain (CPR Spine), School of Sport, Exercise and Rehabilitation Sciences, University of Birmingham, Birmingham B15 2TT, UK.
E-mail address: d.falla@bham.ac.uk (D. Falla).

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can be more evident during dual-task gait, in the current study we aimed to determine whether machine learning algorithms could be used on kinematic data collected during this condition for the purposes of classifying people with and without CNP.

The use of Inertial Measurement Units (IMU) sensors for the study of human motion has been shown to be feasible and reliable [15]. Given the evidence of gait disturbances in people with CNP, we aimed to discriminate between normal and altered gait by extracting characteristic motor features from three IMU sensors. Previous research has shown that motion metrics derived from IMU signals can accurately detect changes during gait in people with musculoskeletal disorders [16–18]. However, many gait studies have examined different time-discrete biomechanical variables (gait speed, step length, acceleration, etc.) [17,19], discarding frequency features that might provide potentially meaningful information. Thus, we incorporated both time and frequency kinematic features into our analysis with the aim of being able to differentiate between asymptomatic individuals and participants with CNP and analyse their discriminative power for the classification task.

In line with recent investigations [12,20], we applied the same data analysis approach in order to identify which gait features and body segments have more discriminative power for the classification. Three supervised algorithms were used to classify between asymptomatic individuals and people with CNP during single- and dual-task gait. A feature selection technique termed Neighbour Component Analysis (NCA) was implemented to analyse the discrimination power of each IMU-derived gait feature since NCA has demonstrated its potential to improve algorithms classification performance in recent work [20–22]. It was anticipated that the results of study will identify relevant gait disturbances in people with CNP which can be identified in a straightforward way (with just three mounted sensors) ultimately simplifying gait analysis in future studies.

2. Methods

2.1. Participants and the experimental protocol

Eighteen asymptomatic individuals and 21 people with CNP were recruited for the study. People with CNP were eligible for the study if they (1) reported their average neck pain intensity over the last four weeks to be greater than 3 out of 10 on a Numerical Rating Scale (NRS) (with two anchor points; 0 = no pain and 10 = worst pain imaginable) [23,24], and (2) had a history of neck pain longer than 3 months. Their perceived neck disability was evaluated using the Neck Disability Index (NDI) [25]. Asymptomatic individuals were eligible if they had no history of neck pain in the last two years that required treatment from a health care practitioner. Exclusion criteria for both groups were previous spinal surgery, rheumatologic condition, current or chronic respiratory condition, or an ongoing compensation claim related to an injury.

All participants received written and verbal information about the study procedures and gave written informed consent before participation. No information regarding the expected results was provided to avoid bias. The study was conducted within a Laboratory at the Centre of Precision Rehabilitation for Spinal Pain (CPR Spine). Ethics approval was obtained from the University of Birmingham and the study was conducted in accordance with the declaration of Helsinki.

Participants were asked to perform single- and dual-task gait, both consisting of walking along a rectilinear path of 8 m at a self-selected speed. For dual-task, participants were additionally asked to turn their heads (from right to the left side or vice versa) as far as they comfortably could whilst they walked. Both tasks were repeated three times by each participant. The tasks are illustrated in Fig. 1.

2.2. Measurements

A wireless IMU system (myoMOTION Research Pro, Noraxon USA Inc.) was used to record gait kinematics. Three IMUs (37.6 mm × 52.0 mm × 18.1 mm; 34 g) were placed with double-sided tape on forehead, upper thoracic spine (T1) and lower thoracic spine (T12). One extra IMU was placed on the right lateral shank, close to the ankle joint to extract the stationary gait phases to divide into gait cycles. Each IMU has a local coordinate system and measures acceleration and angular velocity along the three coordinate axes at a sampling frequency of 100 Hz.

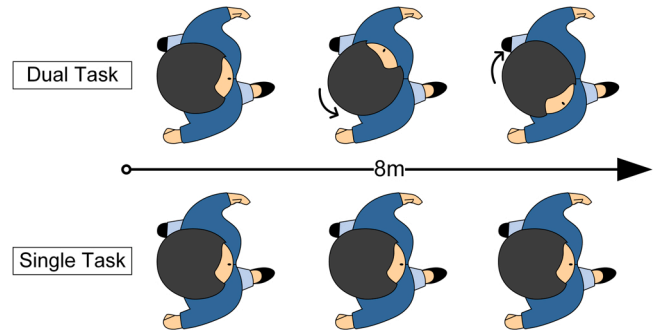

Fig. 1. Tasks performed by the subjects.

Data was acquired using the Noraxon software system (MyoRESEARCH 3.12), which provides a rigid body model tailored to each participants' anthropometric dimensions.

Before each trial, the model was calibrated in the anatomical position. The Noraxon system also incorporates a Kalman filter that automatically filters the raw data.

2.3. Data processing

Data were filtered and segmented into gait cycles. Firstly, zero frequency components were removed by the subtraction of linear trends of gravitational components from the accelerometer data (detrending method) [26] and secondly, a second-order Butterworth filter with a cut-off frequency at 6 Hz was applied [27–29]. For the segmentation, the gait cycle was defined as the time between two successive heel strikes of one leg and then normalized in time to form 101 data points (representing 0–100% of cycle time). For all trials, the initial and final steps were removed, and the averaged trial was extracted for each participant [30].

Once the signals were filtered and segmented, relevant features were extracted from each gait cycle in order to describe the observed gait pattern. A set of time and frequency domain features was selected. Velocity, acceleration, jerk, and smoothness encompassed the time set, and entropy, energy, and power of accelerometer data encompassed the frequency set.

Kinematic features were computed on all sensor axes separately, and then the resultant norm vector was extracted for each one in order to reduce the size of the feature vector and also make it more robust to rotations [31]. All the frequency features we computed by the Fast Fourier Transform and frequency normalized by using a hamming window [32]. For each feature, mean, maximum, and minimum values were extracted to build the feature vector.

Three supervised learning approaches were used to create a binary classification model that relates kinematic features from gait to internalizing classification between participants with and without CNP. Due to the complexity and heterogeneous nature of CNP, it is difficult to choose a single algorithm that fits perfectly for our purpose. For that reason, we used a comparison of three different algorithms which apply parametric and non-parametric approaches; K-Nearest Neighbour (K-NN), Support Vector Machine (SVM), and Linear Discriminant Analysis (LDA) techniques were chosen. K-NN was set with five neighbours and with Euclidian distance. SVM was configurated with radial basis function kernel and box constrain of one. LDA was designed with an equal

predictor covariance treatment among classes and gamma set to 0.2. More information about functionality and configuration of all algorithms can be found in previous work [20].

Exploring the discrimination power of features not only reduces the number of the dataset but also improves the algorithms' generalization performance. Feature selection was made by NCA, a novel non-parametric technique proposed by Goldberger et al. [33]. This method maximizes the performance of the K-NN classification algorithm by computing the expected Leave-One-Out (LOO) classification error over the training data [34]. During the process, NCA makes no assumptions on the class distributions and does not lose any information during the dimensionality reduction process. The NCA algorithm provides a ranking of all features (feature weighting vector) based on their statistical distribution and on their discrimination power for the classification, therefore, the selection of a specific feature or group of features relies on those with higher weights. Those features with a weight greater than 5% of the maximum weight were selected. The optimal regulation parameter was determined to ensure better classification accuracy [34]. In order to observe the NCA's effect, we ran all algorithms twice, one without NCA's feature selection and the other one with feature selection. Fig. 2 illustrates the steps carried out for this analysis.

The performance of the three classification models was assessed using the multiclass confusion matrix to obtain accuracy, sensitivity, and specificity results. For this, the dataset was split into training-validation (85%) and test (15%) sets. A Leave-One-Subject-Out cross-validation (LOSO CV) scheme was adopted to train and validate all models. LOSO CV consists of training on the data from all subjects except for one and validation on the withheld subject's data. With this approach we ensure subject independence [35]. After applying this approach, all models were tested with the unseen remaining data. Statistical analysis was computed to evaluate the normality of the data as well as the differences in age and body mass index (BMI) between groups using independent t-tests.

3. Results

There were no differences between the two groups in age (CNP group: 32.1 ± 8.6 years, control group: 30.1 ± 5.3 years) or BMI (CNP group: 22.9 ± 3.5 kg/m^2, control group: 22.95 ± 3.8 kg/m^2) ($p > 0.05$). In the CNP group, 76% were women and 50% of the control group were women. The average score on the NDI for the CNP group was 15.6 ± 5.9.

The classifiers were first trained with all the extracted features without any feature selection to obtain reference values and observe the effect of the feature selection technique. Table 1 presents the classification results for each algorithm and task before and after the implementation of NCA. We can observe that in all cases, there is an improvement in terms of accuracy, specificity, and sensitivity after the implementation of NCA. This classification improvement highlights the capability of the algorithm to detect discriminative kinematic features that lead the classifiers to a better differentiation between groups.

Table 1
Classification performance for each trajectory obtained on the test set ACCU: accuracy, SPEC: specificity, SENS: sensitivity.

		Single-task	Dual-task
All features			
K-NN	ACCU	55.26%	71.03%
	SPEC	60.00%	72.72%
	SENS	49.98%	68.74%
SVM	ACCU	50.02%	63.15%
	SPEC	54.16%	66.65%
	SENS	42.85%	58.82%
LDA	ACCU	55.24%	63.15%
	SPEC	61.10%	68.40%
	SENS	50.00%	57.87%
Selected features by NCA			
K-NN	ACCU	71.06%	84.22%
	SPEC	77.77%	89.47%
	SENS	66.67%	86.67%
SVM	ACCU	76.30%	86.85%
	SPEC	75.02%	83.30%
	SENS	78.55%	92.85%
LDA	ACCU	68.39%	81.60%
	SPEC	69.56%	79.16%
	SENS	66.66%	85.70%

Overall, whether before or after NCA, the classification performance was always superior for the dual-task gait condition. The best classification performance corresponds to dual- task gait through NCA-SVM algorithms with an accuracy of 86.85%. Successively, we have K-NN and LDA, with 84.22% and 81.60% of accuracy, respectively. The same ranking performance appears for single task gait in which SVM displayed an accuracy of 76.30%, K-NN with 71.06%, and lastly LDA with 68.39%. Moreover, NCA-SVM achieved the highest sensitivity (92.85%) and a high specificity (83.30%), meaning that it correctly identified very high proportions of the true cases (people with CNP) as well as a good proportion of false cases (people without CNP). In this kind of classification, it is more important to prioritize sensitivity over specificity as failing to classify people with CNP is likely to be more relevant than failing to classify asymptomatic individuals.

A boxplot is presented in Fig. 3 in order to show the features' weights learned by NCA over the validation set. This figure illustrates not only the features with higher or lower significance for the classification, but also which body segments encapsulate the most relevant features. In this figure, we can appreciate that for both tasks, the body segment which presents with the greater weights is the head, followed by the lower and upper thoracic spine regions.

In total, the NCA algorithm selected 16 features for single-task gait and 11 features for dual-task gait. Afterwards, we tested these new feature sets to find which subset produces the best classification performance with the minimum number of features. Fig. 4 shows the accuracy of each classifier as a function of the number of features selected by NCA. In the single-task gait, the maximum accuracy of SVM (76.30%) was achieved with five features, followed by K-NN (71.06%) and LDA (68.39%) with four and seven features, respectively. For the dual-task

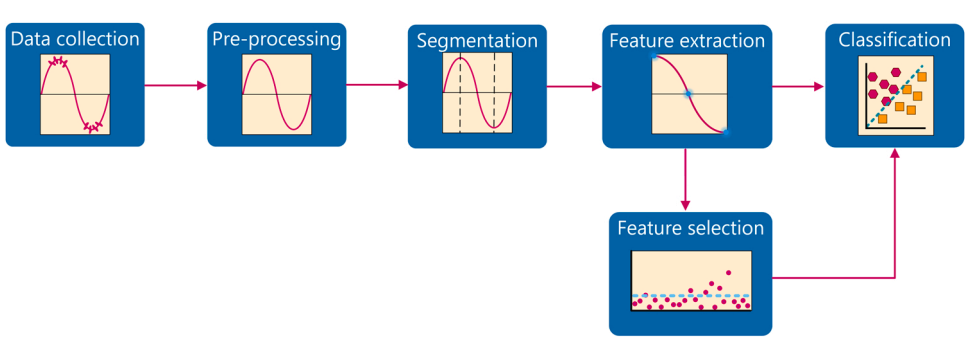

Fig. 2. Data analysis block diagram.

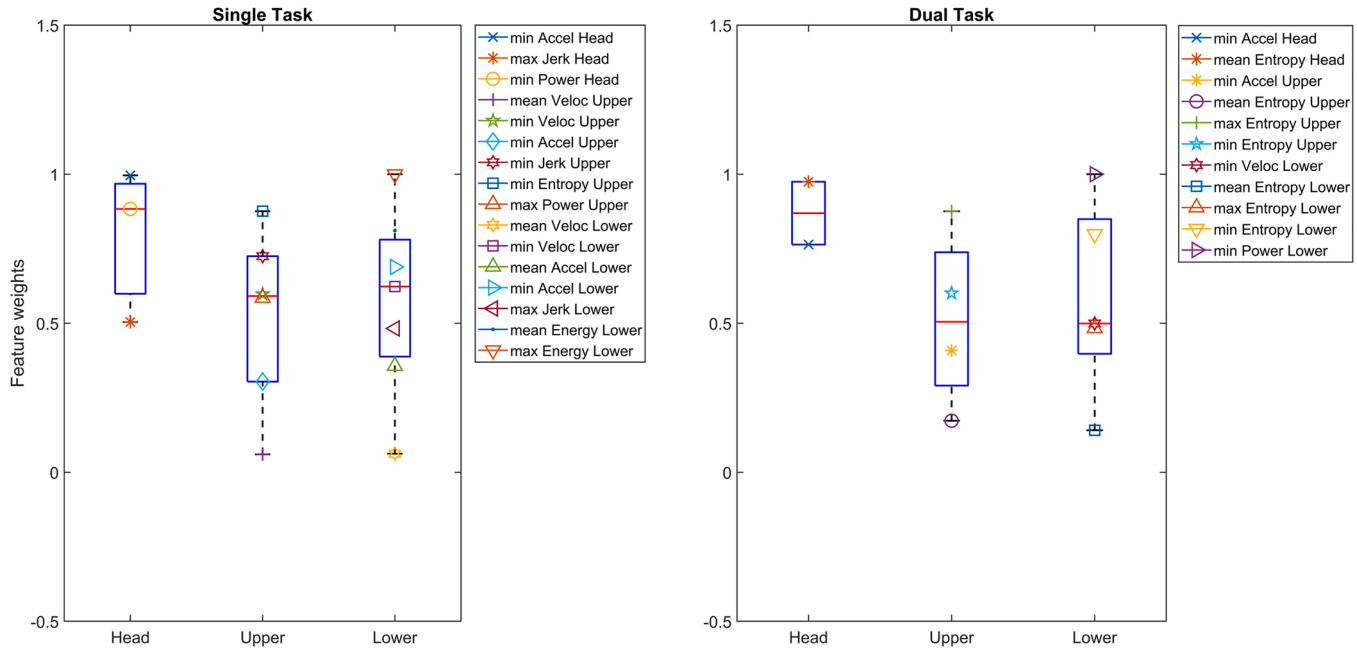

Fig. 3. NCA weights for Single-task (Left) and Dual-task (Right) obtained from the validation set.

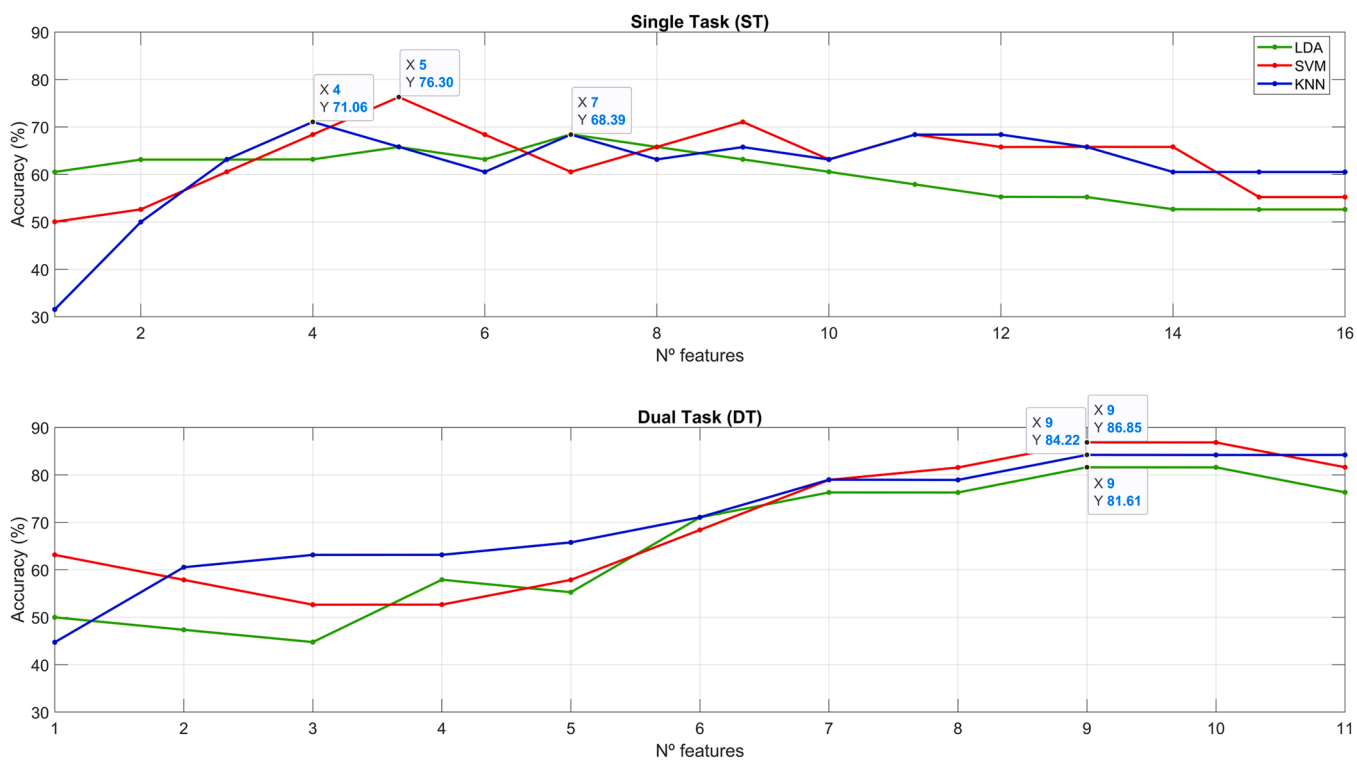

Fig. 4. Accuracy versus the number of features for Single task (Up) and Dual task (Bottom) on the test set.

gait, the maximum accuracy of SVM (86.85%), followed by K-NN (84.22%) and LDA (81.60%) were achieved all by nine features.

All the features selected by NCA, and their weights are listed in Table 2. It can be seen that those features with higher weights correspond to frequency features in both tasks. This underlines the importance of frequency characteristics for the classification. The most represented feature was entropy for dual-task gait and acceleration and velocity for single-task gait. This could be explained due to the greater complexity of the dual-task as both groups could have performed the task slowly therefore differences in speed, acceleration or jerk were not quite noticeable and it is when the frequency features played a key role in the differentiation task.

4. Discussion

In this study we demonstrated the utility of machine learning approaches for the classification of people with and without CNP based on IMU-derived gait features for both single- and dual-task gait. In addition,

Table 2
Features weights. *FW: feature weight, Veloc: velocity, Accel: acceleration.

	Single-task		Dual-task	
Body segments	Features	FW*	Features	FW
Head	Min Accel	0.996	Min Accel	0.763
	Max Jerk	0.504	Mean Entropy	0.974
	Min Power	0.883		
Upper spine	Mean Veloc	0.060	Min Accel	0.408
	Min Veloc	0.597	Mean Entropy	0.172
	Min Accel	0.304	Max Entropy	0.875
	Min Jerk	0.724	Min Entropy	0.600
	Min Entropy	0.875		
	Max Power	0.585		
Lower spine	Mean Veloc	0.062	Min Veloc	0.499
	Min Veloc	0.623	Mean Entropy	0.140
	Mean Accel	0.356	Max Entropy	0.483
	Min Accel	0.688	Min Entropy	0.799
	Max Jerk	0.482	Min Power	1.000
	Mean Energy	0.810		
	Max Energy	1.000		

we have identified the most informative task-dependant features that can play a critical role in classification as well as the relevance of a dual-task condition to challenge motor performance and consequently, emphasize group differences.

4.1. Gait kinematics

Taking advantage of advanced technologies, wearable sensors can be used to measure gait kinematics in a simple manner providing an informative feature space as has been demonstrated in this work.

Several studies have been conducted to identify gait disturbances in people with neurological disorders (Alzheimer's disease [36], Parkinson's disease [37,38], or Stroke [39,40]). As a result, and to address the clinical need to evaluate patients in a simple manner, wearable sensors have been used in combination with machine learning models to objectively assess the functional impact of neurological conditions. This topic has raised a great deal of interest over the last decade [41]. However, these novel methods have not yet been applied in the same way to assess people with musculoskeletal disorders.

Motivated by the fact that people with CNP may present with abnormal movement patterns during gait [4,8,42], in this study for the first time we identified the most informative kinematic gait features based on the data collected using only three wearable sensors, processed using machine learning approaches.

We have observed that conducting a secondary motor task during gait (i.e., dual-task gait) provides a better classification performance than single-task gait. This result was consistent both prior and post the application of the feature selection method (SVM: 76.30% and 86.85%, respectively). This ultimately can be translated into better discrimination between groups. Dual-task gait presents a more demanding manoeuvre in terms of coordination and control, specifically when your range of motion could be limited because of pain. This finding highlights the ability of dual-tasks to challenge motor control and simultaneously emphasize gait changes and differences in people with CNP compared to asymptomatic controls. A similar conclusion was reached in earlier investigations in which it was found that gait disturbances are more strongly associated with a complex gait task than a simple gait task in people with neck pain [43].

The body region that carried the most discriminative information for the classification for both tasks is the head. This result suggests that it may be possible that only one inertial sensor located on the forehead could serve as indicator of gait quality, providing enough information of head-neck kinematics and differentiate between groups.

4.2. Performance of approaches

The classification accuracy achieved by all classifiers after the feature selection technique was remarkably increased. SVM exhibited the highest accuracy, specificity and sensitivity (86.85%, 83.30%, 92.85%, respectively) with only nine features which entail less computational cost, less consumption of time, and a robust classification. The linear classifier LDA showed the lowest accuracy among the three methods in both tasks. This may suggest that the dataset was hardly linearly separable as SVM resulted in a better performance.

The benefits of implementing NCA can be summarized as a reduction of complexity and improving the accuracy of all learning models, by only providing weight-based information of significant features.

4.3. High impact features

Using NCA, extracting informative, independent, and simple features that are able to discriminate between people with and without CNP and simplify the learning process is an essential process for improving the performance of the proposed machine-learning classification analysis. During single-task gait, time-domain features were prevalent including acceleration and velocity. However, frequency features such as energy, entropy, and power provided more discriminative power (higher weights) for the classification using NCA analysis. In contrast, in dual-task gait, the presence of frequency features was higher, but similar to the single-task gait condition, acceleration and velocity were present as well. These results highlight the fact that inertial signals extracted from human gait also provide relevant information in the frequency domain. This has been confirmed by other studies where frequency features improved the outcome in gait analysis [44]. Especially in the dual-task condition, these frequency features played a major role. A possible explanation is that by challenging the nature of the task both groups are forced to walk more carefully, reducing their speed and therefore, making it more difficult to find meaningful differences in those speed-dependant variables.

4.4. Study Limitations

A limitation of this study is the small sample size used (18 healthy subjects and 21 CNP patients) to train and test the supervised algorithms which may limit the generalisability of the results. For that reason, further research is needed with larger cohorts.

A further consideration is that we limited the evaluation of kinematic features to head and spine movement. Although this was purposeful to assess regions that are most likely to be affected in people with neck pain, previous work has shown that gait features such as step length and gait speed can also differ between people with and without chronic neck pain [7–12]. In the current study, the IMU located on the right shank was only used to identify each gait cycle.

5. Conclusion

This paper proposed a classification model designed for accurate classification of people with CNP from asymptomatic people based on IMU-derived gait kinematics collected from only three wearable sensors during gait. A feature selection technique was implemented capable of identifying the most relevant features, improving the performance, and revealing the discriminative power of frequency features for the classification. This study has demonstrated that people with CNP present different kinematic features not only in the time-domain but also in the frequency domain. In addition, it was revealed that gait alterations in people with CNP become more evident due to dual-task interference.

Conflict of interest statement

The researchers report no conflict of interest regarding this study.

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