Low back pain exacerbation is predictable through motif identification in center of pressure time series recorded during dynamic sitting

博士論文

Low back pain exacerbation is predictable through motif identification in center of pressure time series recorded during dynamic sitting

（座位中の圧力中心変化の動的時系列信号解析を通じたモチーフ認識による腰痛増悪の予測）

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Low back pain exacerbation is predictable through motif identification in center of pressure time series recorded during dynamic sitting

A thesis submitted in fulfillment of the requirements for the degree of Doctor of Philosophy (PhD)

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ABBREVIATIONS

LBP: Low back pain

COP: Center of pressure

TICC: Toeplitz inverse covariance-based clustering

MASA: Motif-aware state assignment

PNN: Probabilistic neural networks

PDF: Probabilistic density function

SSA: Social spider algorithm

BIC: Bayesian Information Criterion

ROC curve: Receiver operating characteristic curve

AUC: the area under the ROC curve

E: LBP exacerbated

NC: LBP level did not change

IM: LBP level improved

EMG: Electromyography

1. ABSTRACT

Background: Low back pain (LBP) is a common health problem — sitting on a chair for a prolonged time is considered a significant risk factor. Furthermore, the level of LBP may vary at different times of the day. However, the role of the time-sequence property of sitting behavior in relation to LBP has not been considered. During the dynamic sitting, small changes, such as slight or big sway, have been identified. Therefore, it is possible to identify the motif consisting of such changes, which may be associated with the incidence, exacerbation, or improvement of LBP.

Purpose: To identify motifs associated with the exacerbation of self-reported LBP by continuously measuring the center of pressure (COP) during sitting behavior of office workers that enables prediction of LBP exacerbation.

Methods: Office chairs installed with pressure sensors to a total of 22 office workers (age = 43.4 ± 8.3 years) in Japan. Pressure sensor data were collected during working days and hours (from morning to evening). The participants were asked to answer subjective levels of pain including LBP. COP was calculated from the load level, the changes in COP were analyzed by applying the Toeplitz inverse covariance-based clustering (TICC) analysis, COP changes were categorized into several states. Based on the states, common motifs were identified as a recurring sitting behavior pattern combination of different states by motif-aware state assignment (MASA). Finally, the identified motif was tested as a feature to infer the changing levels of LBP within a day. Changes in the levels of LBP from morning to evening were categorized as exacerbated, did not change or improved based on the survey questions. Here, I present a novel approach based on social spider algorithm (SSA) and probabilistic neural network (PNN) for the prediction of LBP. The specificity and sensitivity of the LBP inference were compared among ten different models, including SSA-PNN.

Result: There exists a common motif, consisting of stable sitting and slight sway. When LBP improved towards the evening, the frequency of motif appearance was higher than both LBP exacerbated ($p < 0.05$) and did not change. The performance of the SSA-PNN optimization was better than that of the other algorithms. Accuracy, precision, recall, and F1-score were 59.2%, 72.5%, 40.9%, and 63.2%, respectively.

Conclusion:

A lower frequency of a common motif of the COP dynamic changes characterized by stable sitting and slight sway was found to be associated with the exacerbation of LBP in the evening. LBP exacerbation is predictable by AI-based analysis of COP changes during the sitting behavior of the office workers.

2. Introduction

Low back pain (LBP) is a highly common issue[1] among people of all ages[2–4], and is generally described as pain, muscle stiffness or rigidity located below the costal margin and above the lower gluteal folds, with or without leg pain (sciatica)[5]. LBP is a common ailment that affects a large percentage of the population, with a lifetime incidence of 58% to 84%[2,6,7]. Even among adolescents, 37% of the subjects reported experiencing LBP monthly or more frequently[4]. In the coming decades, the global burden of LBP is anticipated to rise even more[8]. LBP affects function, societal participation and personal financial well-being in various biophysical, psychological and social ways. LBP is the leading cause of disability in working-age people worldwide, especially in low- and middle-income countries where informal employment is common, and job-changed options are limited[8]. As one of the most common chronic health problems, LBP causes more people to leave the workforce than heart disease, diabetes, hypertension, neoplasm, respiratory disease and asthma combined[9]. People who suffer from this disorder have less wealth than those who do not[10] — when comorbidities are present, this effect is amplified[10]. Older people who retire early because of LBP have approximately 87% less total wealth and income-producing assets than those who remain in full-time employment[11].

LBP could be a result of many factors. Its emergence could be attributed to several psychosocial and physical factors. A systematic review showed that structural changes identified by MRI, such as disc bulge, disc extrusion and spondylolysis were strongly associated with LBP[12]. However, in most cases, the causes of LBP could not be identified and were described as nonspecific[13,14]. Many imaging (radiography, CT scan, and MRI) findings in people with LBP were also present in people who did not have LBP[15]. Furthermore, LBP risk factors include obesity, age, smoking and psychosocial factors (such as depression and stress)[16,17]. In addition to the above-mentioned risk factors, static loading in the office environment may worsen LBP[18], and prolonged static sitting was associated with an increased risk of LBP and an increase in LBP over the last 40 years[19–23].

Sedentary behavior is a class of behaviors characterized by little physical activity or activities that require low energy consumption of less than 1.5 metabolic equivalent units[24]. A study on adult sedentary behavior found that sedentary time spent increased with age, full-time employment, and higher education[25]. A study of 27,637 people aged 15–98 years from 32 European countries showed that the average recorded weekday sitting period was 5.2 h/day (S.D. 184 min/day)[26]. Research conducted in Australia and the UK reported that office staffs spent 68%–70% of a workday and 60%–63% of a non-workday[27,28]. Japanese office workers spent 63% of a workday and 60% of a non-workday sedentary[29]. A study of 1329 sitting workers showed that 201 (15.1%) acknowledged experiencing LBP during the recent week of the survey[30].

However, there exists conflicting evidence regarding the relationship between sedentary behavior and LBP. Two systematic reviews revealed that LBP was not consistent with sedentary lifestyles. They have identified eight high-quality studies, including cohort studies and case-control studies. Except for one cohort study, none of the studies have identified a statistically significant association between sedentary work or sitting at work and LBP[31,32]. Sitting for a longer period may result in the development of LBP, but the incidence rate of LBP development largely varied among the studies ranging from 19.2%–43.6%[33,34]. It is believed that this variability may be due to the dynamic nature of LBP. Even for chronic LBP, patients do not suffer from pain all day long.

Researchers have attempted to identify if a subject had chronic LBP during sitting behavior using several techniques, including artificial intelligence (AI). AI differs from classical statistics. From the feature engineering stage, potential features can often be discovered by data-driven, such as graph models or time series decomposition. Further, the model can often discover features in hyperspace that are difficult to classify from low-dimensional features. Three studies compared electromyography (EMG) recordings from trunk muscles, spinal positions and trunk range of motion between chronic LBP patients and control participants by using neural network and the fuzzy inference system[35–37], with the accuracy of classifying LBP ranged from 83% to 92%. Several studies have examined EMG and trunk motion data to identify chronic LBP by different machine-learning models, with an accuracy higher than 70%[38–46]. Although many previous studies analyzed static traits during sitting[47,48], it has been pointed out that the dynamic nature of LBP had not been considered. It was possible that chronic LBP patients were not suffering from LBP at the time of measurement. LBP does not persist all day long or every day — even the same individual at different times of the day has different levels of LBP. The majority of the LBP episodes are brief and have little or no consequences. Still, recurrent episodes are common, and LBP is increasingly recognized as a long-term condition with a variable process, not a series of unrelated events[8]. There is another problem that previous studies may suffer. LBP in daily life may differ from that identified at laboratory measurements where most of the studies used EMG and body movement in laboratory settings. Measurement and evaluation over a prolonged time of period comparable to daily life are almost impossible. Therefore, currently available non-invasive, unobtrusive and contactless methods, capable of collecting data from the sensors on the chair may be suitable for measurements in a “real-life” setting.

Another limitation in the previous studies focusing on sedentary behavior may be in the assessment of sitting behavior on an aggregate basis, as to determine sitting behavior as a whole. Typically, the evaluation was commonly determined by the total sitting time[47]. This conventional approach conceptualizes sitting activity as a person's static characteristics in a single day. Conversely, some studies have tried to obtain a sitting posture using pressure sensors placed under a chair, armrests and chair backrests[49-51], merely describing the sitting posture, without providing insight into the nature of sitting behavior. Such approaches to characterize sitting behavior overlook the fact that sitting is a highly complex process. As shown in many studies that sitting behavior contains slight sways and big sways[52-55]. Interestingly, two studies reported less frequent postural shifts in individuals with LBP than in healthy individuals[56,57], with just counting postural shifts above a determined threshold level of displacement. A better characterization of sitting behavior in daily life when most of the LBP episodes occur considering the time sequence property of sitting behavior may give us a better understanding of the physiological nature of LBP. Thus, we hypothesized that sitting behavior could be characterized by constant sequences of states derived from various postural changes during sitting. The term "state" refers to an interpretable template that can be repeated frequently. In this study, a "state" was calculated by subsequent time-series clustering of changes of center of pressure (COP), representing a specific action during sitting. The term "motif" consisted of multiple states, defined as patterns that have a similar shape, and yet exhibit nontrivial variability, which may be able to determine the sitting behaviors on a more granular basis: identifying the definition and nature of each motif, consisted of different states.

There also remains an issue in the complexity of data derived from long-term human behaviors, namely sitting in this study. To understand these complex data, each measurement must be labeled as one of the different states. These states are not present as independent events, and the sequence in which they occur is essential. While traditional multiple time-series repetition methods produce several segments of time[58–61], motifs are anticipated to produce multiple cycles of data in multiple time steps. Thus, it is crucial to determine a motif indicating the recurrent events or a sequence of state changes. To this end, I began to use Toeplitz inverse covariance-based clustering (TICC)[62] to split the sitting data into different states. Further, I defined each motif by motif-aware state assignment in noisy time-series data (MASA)[63]. MASA aims to find sequences of measurements that may conform to each motif. MASA differs from previous methods in two ways. First, MASA allows latent motifs with varying lengths and combines the same states into one component of a motif[63], in contrast to uniform approaches that hold a constant length[64]. Second, MASA iterates by re-assigning the original measurement to the updated states using motifs, thereby allowing previously noisy sequences to make a correlation to match a given motif. This makes MASA even more robust as it allows previously noncorrelated sequences to correlate[63].

In the prediction step, I use a probabilistic neural network (PNN) as classifier[63], which is a special type of radial basis function that is significantly faster than backpropagation networks[66]. PNN is based on the probability density function (PDF) and Bayesian classifier[65] which could reduce the likelihood of misclassification[67]. However, there are two limitations in PNN. (1) Relative inaccuracy when training with a small sample size and (2) lack of evaluation of the importance of the input variables. Therefore, to address these limitations, this study adopts an optimized PNN with two parameters: one is the smoothing parameter, representing the spread of the distribution, and the other is the weight of the input variable which changes the shape of PDF so that the contour line is no longer circular but elliptical.

Furthermore, it is crucial to find an optimal value for the weight and smoothing parameters to enhance the performance of the model. Earlier, trial and error methods were commonly used to select the parameters; however, these methods were time-consuming. Recently, reinforcement learning algorithms have become one of the methods for computing parameter selection[68]. Meanwhile, this parameter estimation problem was shown to be solved by nature-based algorithms. With the rapid growth in the size and complexity of modern optimization problems, nature-based computation (e.g., genetic algorithms[69], ant colony optimization[70], and particle swarm optimization[71]) has gained increasing attention as an effective tool for optimization. When compared to traditional optimization techniques, these algorithms were shown to perform well, especially when solving nonconvex optimization problems[72,73]. As a population-based metaheuristic general algorithm, the social spider algorithm (SSA), a state-of-the-art nature-inspired swarm intelligence algorithm based on social spiders, exhibited excellent global optimization performance on benchmark tests[74]. Therefore, whenever the algorithm can locate a relatively small region near the global optimum, SSA was found to be capable. Thus, I used SSA as the optimizer of PNN and inferred the change in LBP using SSA-PNN.

3. Purpose

This study aimed to determine whether the motif consisting of different states identified in the COP changes during sitting behaviors may affect LBP exacerbation. I optimized PNN and used SSA as the optimizer, so that LBP exacerbation based on the COP data collecting could be able to predict. Previous studies have established that sitting behaviors may exhibit particular states. Thus, I hypothesized that 1) there is a common motif consisting of more than two states, and 2) the motif may be related to LBP.

4. Method

4.1 Study design

This study is an observational study of office workers to identify daily exacerbation of low back pain occasionally experienced during their work at the office through the analysis of features in sitting behavior by means of time-series recording of changes in the center of pressure using load cells installed on office chairs. The subjective level of low back pain was checked four times daily at the office during the workdays by means of presenting an electronic questionnaire using a tablet PC. The study participants were recruited at a company and the office was located in downtown Tokyo, in July 2017 after the approval of the study protocol by the Ethical Committee of Tohoku University School of Medicine. The measurement and data collection were performed from October to December 2017 at the office in a restriction-free environment where the study participants worked according to their real assignment in the company.

4.2 Participants

In order to ensure the safety of procedures and to avoid bias on results due to serious disease, the following inclusion criteria were used: office workers who are between 20 and 59 years old when they gave their informed consent were eligible. The exclusion criteria were those who had serious psychiatric, neurological or musculoskeletal diseases (musculoskeletal disorders) that caused low back pain or neck pain, and those whose weight was 80 kg or more.

4.3 Smart chair

Conventional office chairs equipped with load cells and WiFi data transfer units were provided to the study participants who gave full informed consent to the study protocol. The dimension of the conventional office chair purchased was 52 cm wide, 58.5 cm in length and 88.5 cm in height with a single column (Fig. 1). Four load cells were fixed on a metal plate of 260 mm wide and 250 mm in the front-back direction and 3.2 mm thick, in a rectangular formation of 215 mm wide and 200 mm front-back direction so that the geometric center matches that of the metal plate. The bottom surface of the seat frame was firmly attached to the load cells. Each load cell had a capacity of 50 kg driven by 5 volts (D.C.). The calibration of the "smart-chair" was performed in 3 steps to ensure validated output signals. Signals obtained without any weight on the seat were determined as zero level, followed by placing a round metal plate of either 40 kg or 80 kg at the geometric center of the seat. A linear relationship was confirmed within the range of up to 80 kg. The load cells were wired to a Rasberry Pi processor and the data was transferred through a WiFi unit at a transfer rate of 100 Hz, and the data was stored online at Amazon Web Server. The seat height was adjusted for each study participant so that both feet could stably be placed on the floor with the legs upright in a comfortable position without extra stretching.

4.4 Assessment of sitting behavior

In order to assess sitting behavior, spatio-temporal changes in the distribution of pressure across the participants' sitting interface were monitored by the smart chair. The sitting behaviors of office employees, such as leaning in various directions, leaving the chair and swaying can be adequately represented by COP. Therefore, we used COP to identify the sitting behavior, calculated as the Eq. 1:

$$\text{COP }(x,y) = \frac{A1(-1,1)+A2(-1,-1)+A3(1,1)+A4(1,-1)}{4} \quad (1),$$

here, the A1 (Front-Left), A2 (Back-Left), A3 (Front-right) and A4 (Back-Right) indicate the values from the sensors. Since this study aimed to identify the motif of sitting behavior instead of the details of physical activities, therefore data were downsampled to 1 Hz, i.e., I cut the sampling rate based on the first timestamp to 1 sample per second.

4.5 Assessment of subjective symptoms

This study focused on changes in the subjective levels of LBP localized below the costal margin and above the inferior gluteal folds, neck pain, satiety and sleepiness. All the subjective levels were determined using a modified Likert scale of 0 to 10 where 0 represented no pain, hungry, or not sleepy and 10 represented the worst pain, full or sleepy. The questionnaire was automatically delivered at regular times every day (9:00, 11:30, 14:00, 17:00) on a tablet PC provided in this study for each participant. Whenever the participants arrived at the office after 9:00, they were asked to answer the questionnaire whenever they started working. Whenever they had to stay in the office after 17:00, they were asked to answer the questionnaire before they left the office. The change in the level of LBP was defined by subtracting the end-of-day score from the morning score. A negative value indicated LBP exacerbated, 0 indicated no change, and a positive value indicated improvement of LBP. The levels of other subjective symptoms were also assessed in a similar manner.

4.6 Relevant features

Thus, in this study, sex, sitting time, motif occurrence number, level of sleepiness and satiety after breakfast were selected to classify changes in LBP. These features were shown to be sensitive to shifts in LBP. Previous studies have identified that gender[75], the degree of sleepiness[76-78], and how full breakfast[79] may potentially affect the level of LBP of the participants.

4.7 Data analyses

In the aforementioned time-series, TICC performs simultaneous segmentation and clustering on the siting behavior data, the motifs were discovered by MASA, and prediction by SSA-PNN (Fig. 2). The broad collection of time-series data can be represented by a small number of sitting behaviors after these motifs are recognized.

4.7.1 Clustering by TICC

TICC is a model-based subsequence clustering technique for multivariate time series to discover recurring patterns in temporal data. It assumes that each state (cluster) has a multilayer correlation network, or a Markov random field (MRF) that contains both intra-layer and inter-layer edges, which is specified for each cluster. MRF is a probability distribution model which emphasizes the correlation instead of the distance. Therefore, TICC is not affected by the sitting position. In this study, the states are described as the interrelationships between observations of COP, which can find accurate and interpretable structures of sitting behaviors without the constraint of temporal consistency.

As defined by TICC, the time series of T sequential observations,

$$x_{\text{orig}} = \begin{bmatrix} | & | & | & & | \\ x_1 & x_2 & x_3 & \dots & x_T \\ | & | & | & & | \end{bmatrix},$$

where $x_i \in R^n$ is the multivariate i-th observation. The objective is to cluster these T observations into K clusters. TICC focuses on the clustering of a short size series $w \ll T$ which ends at t. The $x_{t-w+1},...,x_t$ observations are built into an nw-dimensional vector X_t . Therefore, a new sequence from X_1 to X_t is created, which is a helpful medium for each T observations to provide proper context. The TICC approach therefore does not cluster the observations directly, but clusters these subsequences with $X_t,...,X_t$. Specifically, TICC constrains the Θ_i' s, the inverse covariances, to be block Toeplitz. Thus, each $nw \times nw$ matrix can be expressed in the following form,

$$\Theta_i = \begin{bmatrix} A^{(0)} & \left(A^{(1)}\right)^T & \left(A^{(2)}\right)^T & \cdots & \cdots & \left(A^{(w-1)}\right)^T \\ A^{(1)} & A^{(0)} & \left(A^{(1)}\right)^T & \ddots & & \vdots \\ A^{(2)} & A^{(1)} & \ddots & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & \left(A^{(1)}\right)^T & \left(A^{(2)}\right)^T \\ \vdots & & \ddots & A^{(1)} & A^{(0)} & \left(A^{(1)}\right)^T \\ A^{(w-1)} & \cdots & \cdots & A^{(2)} & A^{(1)} & A^{(0)} \end{bmatrix},$$

where $A^{(0)}, A^{(1)}, \ldots, A^{(w-1)} \in R^{n\times n}$. $A^{(0)}$ sub-block indicates the intra-time partial interdependencies, so that $A_{ij}^{(0)}$ defines the interrelationship between concurrent values of sensor i and sensor j (e.g., the change of COP in two directions). TICC's purpose is to solve the K inverse covariances $\mathbf{\Theta} = \{\Theta_1,..., \Theta_K\}$and to get the corresponding point assignment sets $\boldsymbol{P} = \{P_1,...,P_K\}$ ($P_i \subset \{1,2,...,T\}$), this leads to an optimization problem in which the following function is to be minimized, as eq. 2:

$$\underset{\Theta\in\mathcal{T},\mathbf{P}}{\arg min} \sum_{i=1}^{K} [\overbrace{\|\lambda \circ \Theta_i\|_1}^{\text{sparsity}} + \sum_{X_t\in P_i} (\overbrace{-\ell\ell(X_t, \Theta_i)}^{\text{log likelihood}} + \overbrace{\beta\mathbb{1}\{X_{t-1} \notin P_i\}}^{\text{temporal consistency}})] \quad (2),$$

here, $\mathcal{T}$ is the set of symmetric block Toeplitz $nw \times nw$ matrices and $\|\lambda \circ \Theta_i\|_1$ is an ℓ_1-norm penalty of the Hadamard (elementwise) product to incentivize a sparse inverse covariance (where $\lambda \in R^{nw\times nw}$ is a regularization parameter). Additionally, $\ell\ell(X_t, \Theta_i)$ is the log-likelihood that X_t came from cluster i, β is a parameter that enforces temporal consistency, and $\mathbb{1}\{X_{t-1} \notin P_i\}$ is an indicator function checking whether neighboring points are assigned to the same cluster. The TICC problem is solved through alternating minimization, using a variation of the EM algorithm.

4.7.2 Discovering motif by MASA

In noisy time-series results, MASA is used for discovering common motifs and leveraging those motifs to assign states to measurements more robustly. It aims to (1) discover motifs in time-series data that recognize important recurring and length-varying trends and (2) assume that these trends require consecutive measures of time. MASA defines a motif as a sequence of corresponding state assignments and provides a sequence of consecutive measurements, where all neighboring occurrences of the same state are combined into one (MASA defines a time-varying hidden Markov model (HMM) to model the entire sequence of measurements X). Therefore, states are ordered in the motif, however the number of consecutive occurrences of each state can differ between motif instances. To this end, each motif is represented by a pair (m,q), where m is the motif, and q is a related list of instances of the motif. In the dataset, a motif instance implies the occurrence of the motif. In this system, I implement the following motif constraints:

(1) The m motif must contain at least three states: $|m| > 2$.

(2) At least L times must appear for a motif m: $|q| > L$.

(3) Motif instances do not overlap at most one motif can only belong to each measurement.

As motifs with two or fewer states are not very insightful outside the clustering, MASA encourages the first restriction. The runtime is supported by the second constraint – I can save time by exploring motifs that are more frequent. Because I am only interested in frequent patterns, I do not need a motif for every measurement.

Since the states of sitting may occur in a particular sequence (like a motif), MASA is sufficient to obtain the motif from states of sitting behaviors. MASA seeks to solve for Θ (In this method, state model defined using TICC model), *S* and *M*, by optimizing the following objective (subject to the above constraints) as Eq. 3:

$$\max_{\Theta,S,\mathrm{M}} \sum_{i=1}^{T} (\log\ P_{\Theta}(X_i \mid S_i) - \beta \mathbb{1}\{S_{i-1} \neq S_i\} + \log\ \gamma \mathbb{1}\{S_i \notin \mathbf{M}\}) + \Psi(\mathbf{M}) - R(\Theta) \quad (3),$$

here, X_i is the measurement at time *i*, which has the assigned state S_i, and MASA defines the probability P_Θ (X_i| S_i). The β term is a hyper-parameter that encourages neighboring measurements to be assigned to the same state. The γ parameter, $0 \leq \gamma \leq 1$, defines the cost of not assigning a measurement to a motif instance. Lower γ values indicate a harsher penalty for a measurement that does not conform to any motif. The term Ψ refers to a scoring metric that measures the strength of this motif based on how often they appear in the dataset. R(Θ) is a regularization penalty on the state model parameters Θ, which formulated the problem of motif discovery as a major optimization problem and solved by using an expectation-maximization approach.

Considering the interpretability of results, the time to maintain the state, I set the window size to 5 s (five samples). Refer to the paper about the TICC and MASA[62,63], as an empirical criterion for assessing the optimization model and the relevant clustering outcomes, I used the Bayesian Information Criteria (BIC). Finally, I used strict rules to obtain the states, the number of clusters K was 4, the penalty factor β was selected as 50, and the regularization parameter λ was selected as 0.001.

4.7.3 Prediction by SSA-PNN

I proposed an optimized PNN. First, a set of random real numbers is generated for the weights and smoothing parameters from SSA[74]. Second, data were split into six sets — five sets were used as training datasets for training the model, and one set of the test dataset was used to evaluate the accuracy and classification effectiveness of the model. In the training set, I further used four datasets for training and one for validation of the five datasets. This process fits five models on different but partially overlapping training sets and applies a set of parameters generated by SSA to these five models simultaneously. Subsequently, it evaluates them on the non-overlapping validation set and uses the cross-entropy from the validation set as loss functions. Compared to a straightforward training/test split, the main benefit of this approach is the built-in cross-validation to obtain parameters with more generalization power capability, and thus, less bias at smaller sample sizes. However, the disadvantage is that it can significantly increase the training time of the model. Finally, SSA obtains the optimal tuning parameter values that can be applied to a fully independent test set to assess the model in an unbiased manner. In addition, if the smoothing parameter of PNN is lower than 0.1, overfitting becomes likely.

Therefore, I use the social spider algorithm as an optimizer[74] to search the smoothing parameters and weights in a modified PNN and tune PNN automatically, demonstrating the applicability of a PNN-based model for decision-making in the classification process. I sought to solve for ω and σ by optimizing the following objective subject, as shown in Eq. 4:

$$\omega_i^*, \sigma^* = \arg\ min \frac{1}{K}\sum_{k=1}^{K} L_k \quad (4),$$

where ω_i represents the i-th input variable weight, σ is the standard deviation of the Gaussian function that is equivalent to the smoothing parameter in PNN, K is the number of folds in the training set, and L_k represents the loss function of the k-th fold. Cross-entropy is a better measure than MSE for classification, as the decision boundary in a classification task is substantial (in comparison with regression); therefore, I used categorical cross-entropy as the cost function, as shown in Eq. 5:

$$L = \frac{1}{N}\sum_i -\sum_{g=1}^{M} y_{ig}\log\left(p_{ig}(x_i \mid c_g)\right) \quad (5),$$

where x represents the test data vectors; y_{ig} represents the indicator variable (0 or 1); if the category is the same as the category of sample i, it is 1; otherwise it is 0. M is the number of clusters. The general classification problem is to determine the category membership of a multivariate sample data (i.e., a p-dimensional random vector x) into one of g possible groups C_g, based on a set of measurements. Generally, the probabilistic density function is a normal probabilistic density function, as shown in Eq. 6:

$$p_{ig}(x_i \mid c_g) = \frac{1}{(2\pi)^{n/2}\sigma^n}\exp\left(-\frac{\left(x_j - x_{ij}^{(g)}\right)^2}{2\sigma^2}\right) \quad (6),$$

Eq. 5 shows that the only manipulating parameter is the smoothing parameter. In this study, for the smoothing parameter and multiple weights, and as I tested, if σ is smaller than 0.1, the training set overfits, then Eq. 5 is developed into Eq. 7:

$$p_{ig}(x_i \mid c_g) = \frac{1}{(2\pi)^{n/2}\sigma^n}\cdot\frac{1}{l_g}\cdot\sum_{i=1}^{l_g}\exp\left(-\sum_{j=1}^{n}\frac{\left(\omega_j x_j - \omega_j x_{ij}^{(g)}\right)^2}{2\sigma^2}\right) \quad (7),$$

where n is the dimension of the input data, that is, the number of attributes, where x_j represents the value of *the* j-th input variable in the testing sample, and $x_{ij}^{(g)}$ represents the j-th input variable of the i-th sample of Category g in the sample base. Notably, determining the class number of new input data is based on the results of the Parzen window. Parzen window is the average probability of input data x_j related to all training samples in each class $x^{(g)}{}_{ij}$ for n attributes. l_g is the number of training probability of input data x_j related to all training samples in each class x_{ij} for n attributes samples that belong to class g. Finally, the fourth layer determines the class of unknown input data that regard to the highest p_{ig} (x_i | c_g).

Furthermore, nine commonly used models (Ridge Regression, Linear Discriminant Analysis, Logistic Regression, Support Vector Machine, K Nearest Neighbors, Extreme Gradient Boosting, Adaptive Boosting, Random Forest, Gradient Boosting) were trained to compare the performance. Because of the small sample size, after tuning the hyperparameter, I set fixed hyperparameters for each model (supplementary materials, list 1) and repeat stratified 6-fold cross-validation 200 times.

4.8 Statistical analyses

The occurrence rate of the common motif in three LBP change conditions was checked for normal distribution and homogeneity of variance. A non-parametric method for comparing two or more independent samples (Kruskal-Wallis test) was done. When significant differences were detected, the post-hoc comparisons (Dunn's test) were performed. The level of significance was determined as p-value < 0.05.

In this paper, all the preprocessing, feature engineering, analysis and visualization were implemented in Python 3.7.1.

5. Results

I excluded participants who did not fill in the questionnaire (n=2) and sit on the chair for less than 20 min (n=6). After these exclusions, there were 22 participants in total, and the participants' demographic profile is presented in Table 1. The total number of days recorded was 90. Each participant provided records for 4.1 days on average. I classified participants into four categories according to the changes in the levels of LBP in the recorded days. Three subjects (13.6 %) experienced an exacerbation of LBP in all the recorded days, eight participants experienced no change in the level of LBP, six participants experienced both the exacerbation of LBP, and no change, five participants experienced the exacerbation, no change and improvement of LBP in the recorded days, as shown in Table 2. Furthermore, Table 3 shows the changes in LBP for all samples, revealing that when LBP exacerbated, sitting time was longer than other groups. There was a clear trend of increasing the common motif from LBP. For both levels of sleepiness and fullness after breakfast, the no change group exhibited the highest score.

The results obtained from the preliminary analysis of BIC are shown in Table 4, which the penalty factor β was 50, and the regularization parameter λ was 0.001. To reiterate, previous research showed that there are more than three states from sitting behavior; thus, I set K from 4 to 10. I can infer 4 with the smallest BIC value, indicates the best number of states. Therefore, in this study, the states of sitting behavior of the office workers were determined to be 4. Otherwise, it may undermine sensitivity and physiological interpretability.

The states of COP are used to reflect the specific pattern from sitting behavior, such as leaving the chair, stable sitting, slight sway and big sway (Fig. 3). Although the states vary slightly among state 1, state 2 and state 3, showing the characteristics of different states of sitting behavior. State 1 indicates stable sitting behavior. State 2 implies slight sway; in general, it was similar to many small actions, such as small stretch or rotation. State 3 indicates big sway. In state 3, the subjects moved significantly in both directions. State 4 indicates the participant left the chair. Furthermore, as Fig. 3 shows, the common motif consists of state 1 (stable sitting) and state 2 (slight sway), I found that 91.1% (82/90) of days had this motif. This indicates a series of complex actions that have a specific sequence.

The sitting behavior data were labeled as four states, and a common motif consists of two states. Subsequently, I used the occurrence number of the motif, sitting time, and other features such as gender, sleepy degree and how full breakfast was inferring to the change of LBP from the morning to night. The output class of the confusion matrix represents the prediction of the PNN-SSA model, enabling it to quickly distinguish confusion between different classes of changes in LBP (Fig. 4). In this study, the normalized confusion matrix and confusion matrix were used to achieve a more visual representation. Each matrix column indicates the predicted label at an inference level of LBP, and each row indicates the actual class. The values of the diagonal elements represent the proportions of correct inference levels. Fig. 4(a) shows the number of predictions that are correct, LBP has the highest probability of misclassification. Fig. 4(b) shows the accuracy of SSA-PNN at three levels. SSA-PNN yielded average accuracies of 65%, 81%, and 14% for worse, no change and better respectively. The performance of predicting LBP level improved was not as good as the other two conditions. This might be attributed that I defined the change of LBP by using the morning score of LBP minus the night score, and most of the scores were very close to 0 which indicates LBP level did not change, physical conditions of no change and got better are similar were surmised. Therefore, the accuracy of LBP level improved has declined.

The ROC curve was constructed to test the quality of the model as a prediction tool. I used the area under the ROC curve (AUC) which was calculated based on all possible cutoff values to evaluate the inference performance of SSA-PNN. Fig. 5 depicts that SSA-PNN had an acceptable ability to infer LBP. The macro-average AUC was 0.77, AUC in LBP exacerbated, no change and improved were 0.72, 0.67 and 0.90, respectively.

The results of the performance of the proposed algorithms show a more detailed interpretation, which was evaluated by mean accuracy, weighted precision, weighted recall, and weighted F1 score, as shown in Table 5. Based on data, cross-validation was performed by applying the 6-fold cross-validation model 200 times. In essence, the SSA-PNN and Extreme Gradient Boosting yielded better overall performance on most optimization problems than other algorithms. However, the other methods exhibited very poor classification rates. For this small dataset, SSA-PNN had high levels of classification performance. However, Support Vector Machine had the best recall results compared with the other algorithms (44.3 %). In general, SSA-PNN exhibits the best adaptability for small datasets.

Fig. 6 shows the performance of SSA with 10 epochs. It was used as the validation set to obtain σ and ω. In this figure, the smaller the value of the performance, the better performance of the neural network. There was a sufficient gain in performance until the 2nd epoch.

Fig. 7 presents the results obtained from the preliminary analysis of sitting behavior. The data did not follow a normal distribution, and the variance was not homogeneous. Significant differences were observed between the three groups ($p = 0.027$; Kruskal-Wallis test), the occurrence rate of the common motif identified in the condition of LBP level improved was higher compared with exacerbated ($p = 0.019$; Dunn's test) and did not change.

6. Discussion

This study used cross-validation in a new way. In contrast to evaluating the model performance, this study used five folds to evaluate the generalization of parameters and fixed each set of parameters obtained from SSA to find a set of smoothing and weighting parameters with the best generalization performance on the k sub-dataset. Therefore, the parameter had the best generalization in the five folders. Thus, we used this model to predict the exacerbation of LBP during sitting behavior in real life.

Although no previous studies have examined the motif in sitting behavior, many previous studies have examined the association of sitting behavior with LBP. Recently, ideal workplace sitting posture and sitting behavior have been widely discussed in the literature. The long-standing doctrine of an optimal seating posture that is "as upright as possible" has been highly disputed. The principle of "dynamic sitting" has been slowly substituted, where sitting postures were identified to continuously change[80,81]. However, O'Sullivan in his systematic review concluded that dynamic sitting approaches are not effective as a stand-alone management approach for LBP[48]. This conclusion could have been generated by ignoring the potential nature that some individuals have more dynamic sitting behavior (like motif), whereas others have less.

The current study is the first to report the motif of sitting behaviors, which consists of stable sitting and slight sway — it is not a type of sitting posture but a dynamic sitting behavior that may alleviate LBP. Perhaps the most critical finding is that this motif has a positive effect on LBP. These results are consistent with the ideas presented in some review articles of LBP[80,81]. The suggestions recommended that a healthy sitting posture are (1) the best thought of as an active, not a static phenomenon, regularly interspersed with moving, (2) the optimal sitting posture, and (3) it helps with lumbar postural health and LBP prevention. In addition, studies have reported less frequent postural shifts in individuals with chronic LBP than in healthy individuals[49,50]. Notably, this result may be explained by the shift of stable sitting and slight sway, similar to a movement in the different parts of the trunk muscles, which may alleviate LBP[81]. These results corroborate the findings of a previous in which prolonged static contractions of trunk muscles could lead to an increased risk of injury[82].

In contrast, postural modification has been shown to increase the saturation of subcutaneous oxygen, which positively affects tissue viability[83]. Therefore, combined with stable sitting and slight sway, this motif may alleviate LBP. After an in-depth analysis, we found that the motif is always less than 3 min, which is like a fundamental unit. It can be extended as a longer motif with the same component and sequence. However, the mechanism by which sitting behavior exhibits this motif was still now known, and I speculate that in unconscious states, the nervous system may be controlling the trunk during sitting behavior for self-protection.

As aforementioned, the motif consists of stable sitting and slight sway that positively affects LBP. These results correlate with a previous study showing that the range of COP displacement in both directions and lumbar curvature were positively correlated with LBP[55]. First, sitting compresses the intervertebral disc, creating hydrostatic pressure in the nucleus by the annulus and adjoining vertebral bodies[84]. The amount of hydrostatic pressure within the nucleus is affected by the number of sits[84]. Therefore, stable sitting and slight sway may be adjusting such pressure in the intervertebral disc. Second, it may be argued that comfortable sitting will preserve lumbar lordosis and transfer the forces acting on the lumbar vertebrae from the intervertebral discs to the lower margins of the articular surfaces of the zygapophysial joints, minimizing the effect of creeping intervertebral discs[57]. Third, slight sway shifts a portion of the body weight, thereby reducing the load of back muscles[54]. Following the present results, previous studies have demonstrated that relative to the upper and lower thoracic areas, the non-pain participants displayed a less lateral bent positional shift in the mid-thoracic region. The participants developed transient pain that showed higher muscle activations in the abdominal muscles. In addition, poor to moderate positive associations between rated pain and low back muscle activation were found[35]. However, with small sample size, caution must be applied, as the findings are subject to the selection bias. Thus, it may be inferred that during working hours, stable sitting and slight sway may positively affect LBP.

I also identified two states and many motifs from the sitting behavior. For the other two states, one was absent from the chair; the subjects might have left the chair for lunch or for meetings at a different place. The other state indicates a big sway, which is not the component of the common motif. However, it may indirectly confirm the association between sitting behavior and LBP. Previous research showed that all participants experienced the highest discomfort in the relaxed slouching sitting posture, which is similar to a big sway[85]. As I mentioned, the increase in the degree of variability in the sitting posture is interrelated with the increase in perceived discomfort[55]. Notably, this effect may be clarified because those who developed pain had larger L1/L2 intervertebral angles, larger pelvic incidences, and sacral slpoes[86]. In contrast, the flexion-relaxation phenomenon in the relaxed slouching sitting posture caused the bodyweight to produce mechanical loading on passive tissues[87]. Furthermore, many motifs consisted of two or more states. Most of these motifs are not as common as the motif I proposed, and I speculate that these motifs highly depend on each individual's characteristic or personality, and there are still several motifs that may reflect LBP. Therefore, it seems that further research can perform clustering based on motifs caused by individual differences to identify a tighter relationship between LBP and such sitting behavior.

Despite these promising results, the questions remained. First, this sample of subjects was likely not large enough to represent the population's vast heterogeneity; caution must be applied, as the findings might not be applicable to the entire population. However, application of the same method, it is possible to collect more data and improve the model performance. Second, it is better to use a generative model for data derived small sample size. For the big data set, discriminate and ensemble models may also have good performance.

7. Conclusion

This study proposed a method of predicting LBP exacerbation of office workers in a "real world" office environment, LBP exacerbation is predictable through motif identification in center of pressure time series recorded during dynamic sitting. I split the time-series data of COP changes into four states and used MASA to find out the common motif consisting of stable sitting and slight sway, which positively affect LBP. I used the motif as one of the features to determine the changes in LBP by SSA-PNN, which had better performance compared with the other nine commonly used algorithms. The contribution of this study is to confirm the nature of sitting behavior, which has significant implications for understanding LBP and sitting behavior. Further studies are required to validate the effect of this motif on LBP; large randomized controlled trials could provide more definitive evidence.

8. References

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9. Figures

Fig. 1. Set-up for the sitting behavior measurements. Participants seated on the chair with 4 pressure sensors and were asked to work as usual, data was collected using the same office chair during working.

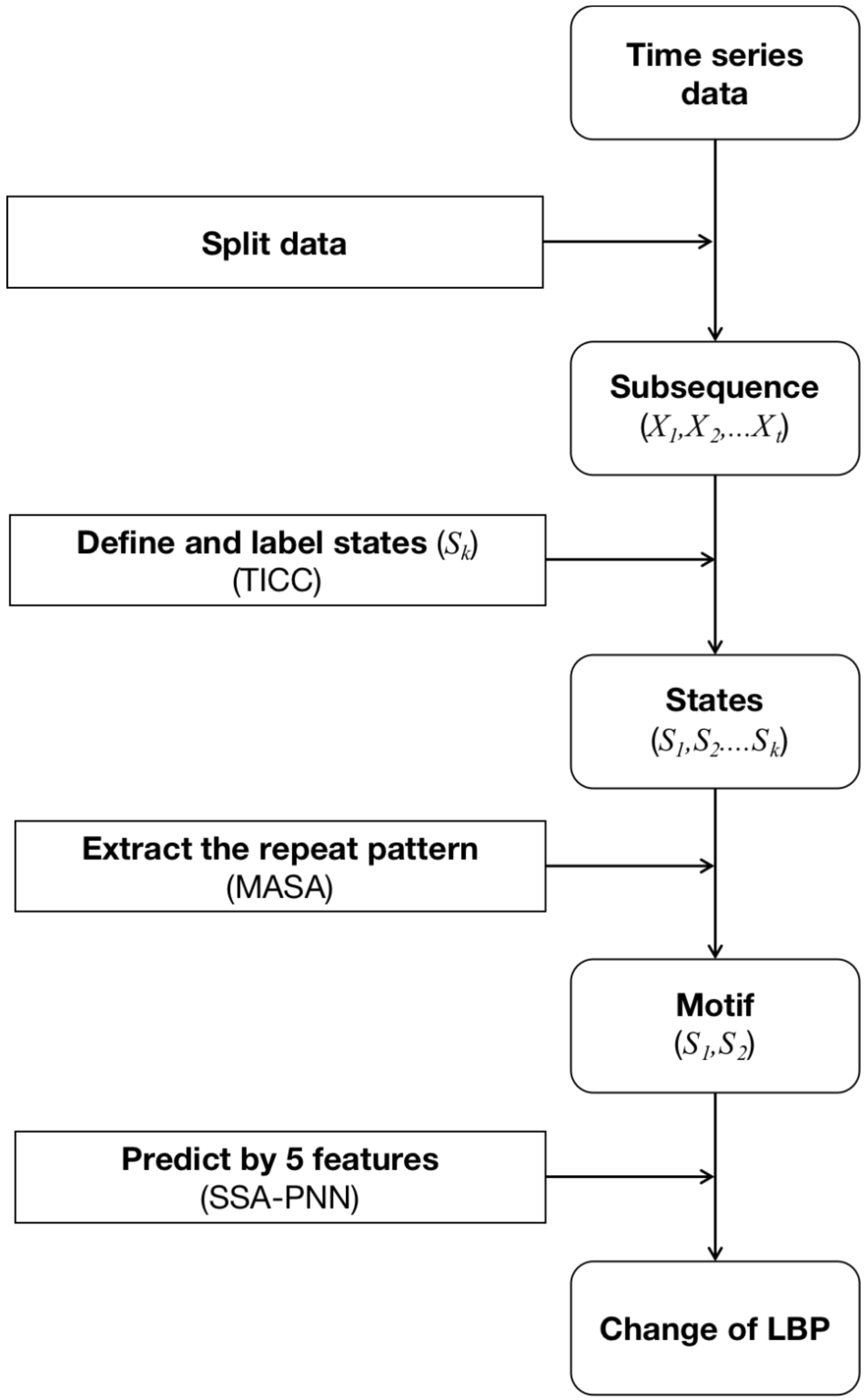

Fig. 2 The framework of the data analysis.

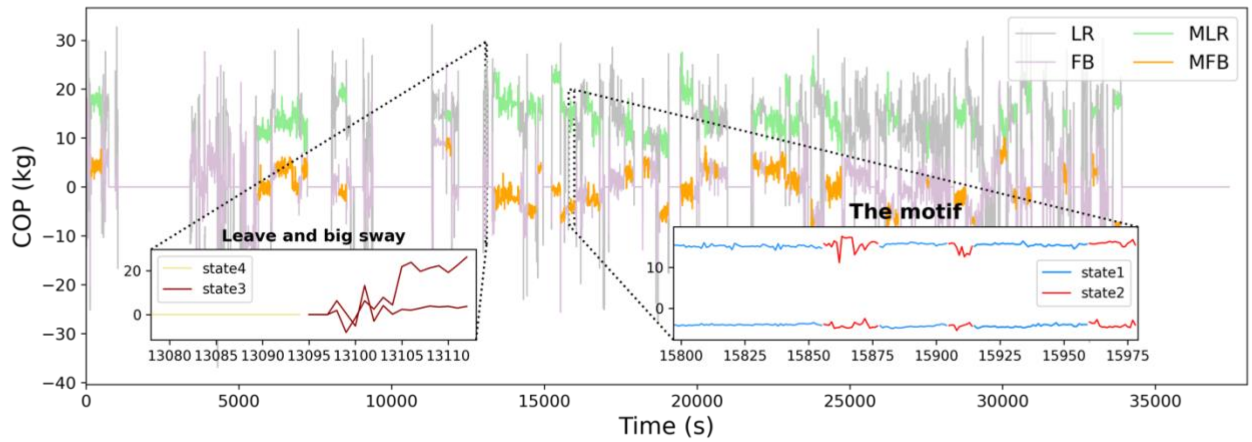

Fig. 3. The common motif. This study used MASA to extract the most common motif from sitting behavior. LR: the change of COP in left and right; FB: the change of COP in forward and backward; MLR: the change of COP in left and right during the motif; MFB: the change of COP in forward and backward during the motif

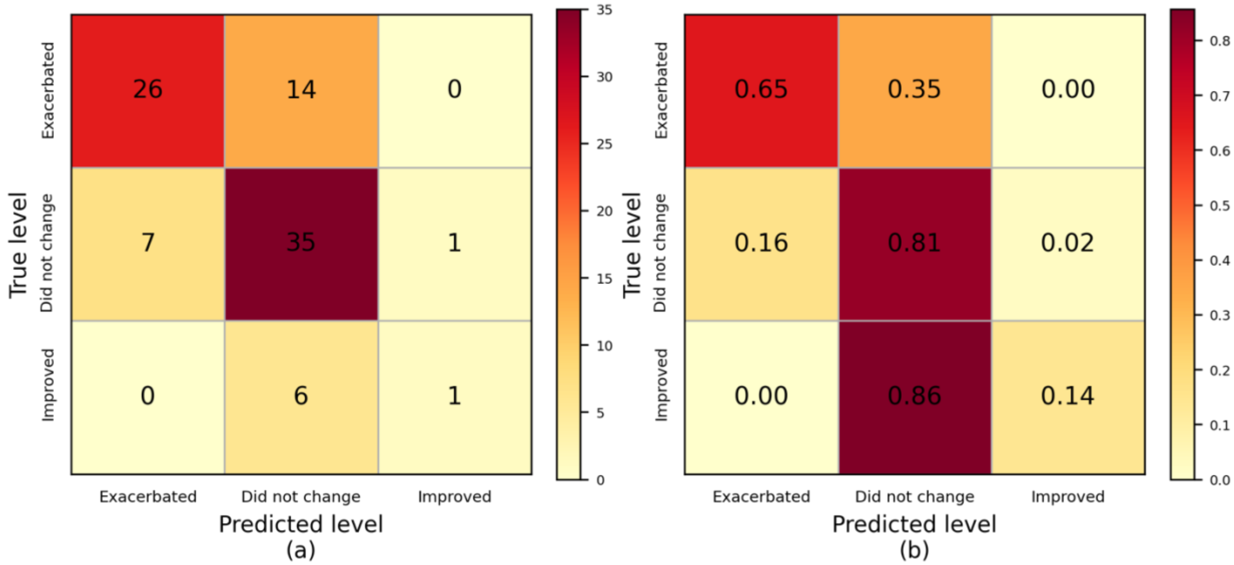

Fig. 4. The confusion matrix of SSA-PNN. (a): the confusion matrix of LBP prediction. (b): the normalized confusion. The plots revealed the performance of identifying various levels of LBP. Among them, “Did not change” had a better result.

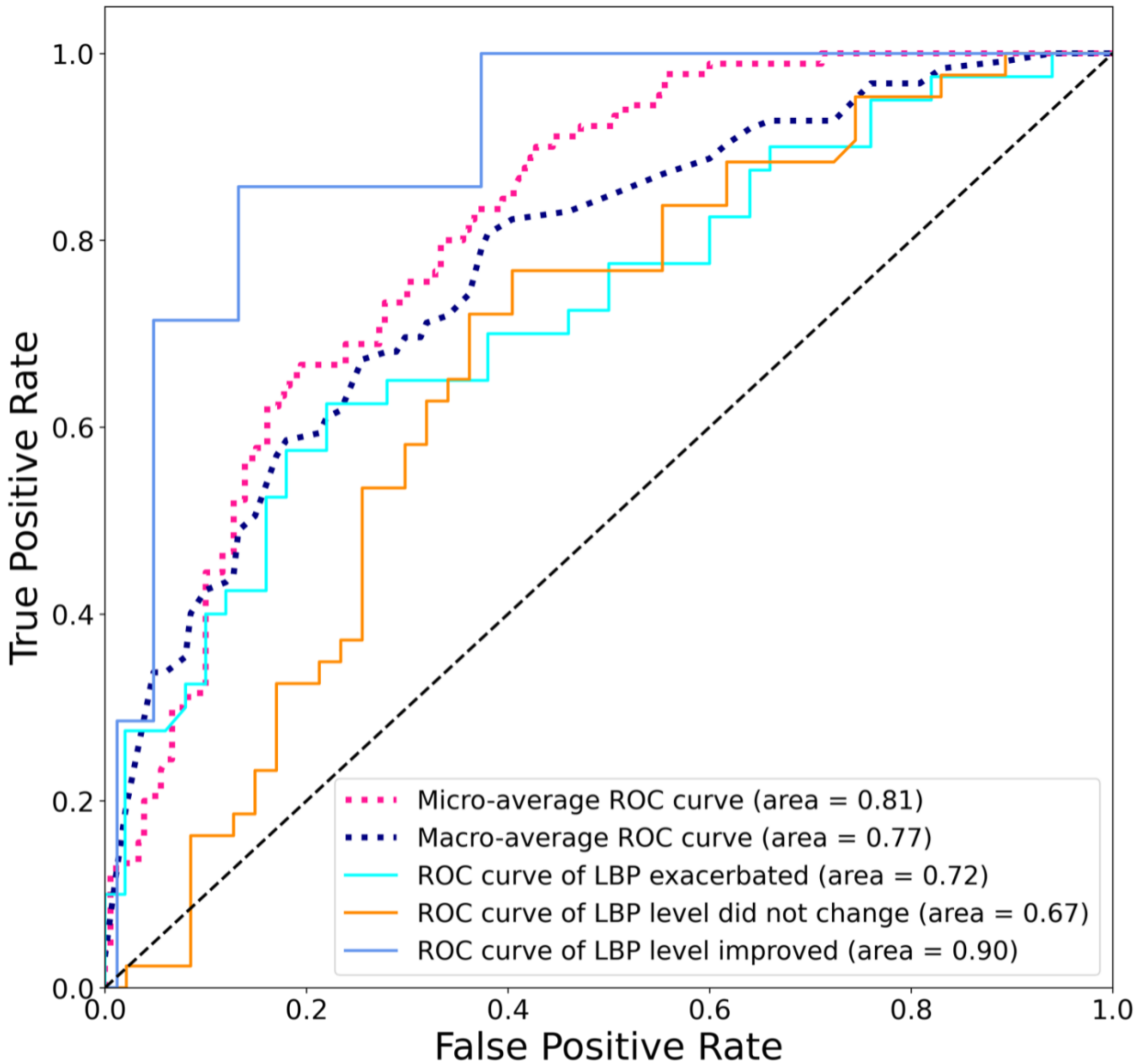

Fig. 5. ROC curves of SSA-PNN. AUC for each ROC curve is provided in the parentheses. The prediction of LBP level improved achieved a better performance (ROC area: 0.90) as compared to the others.

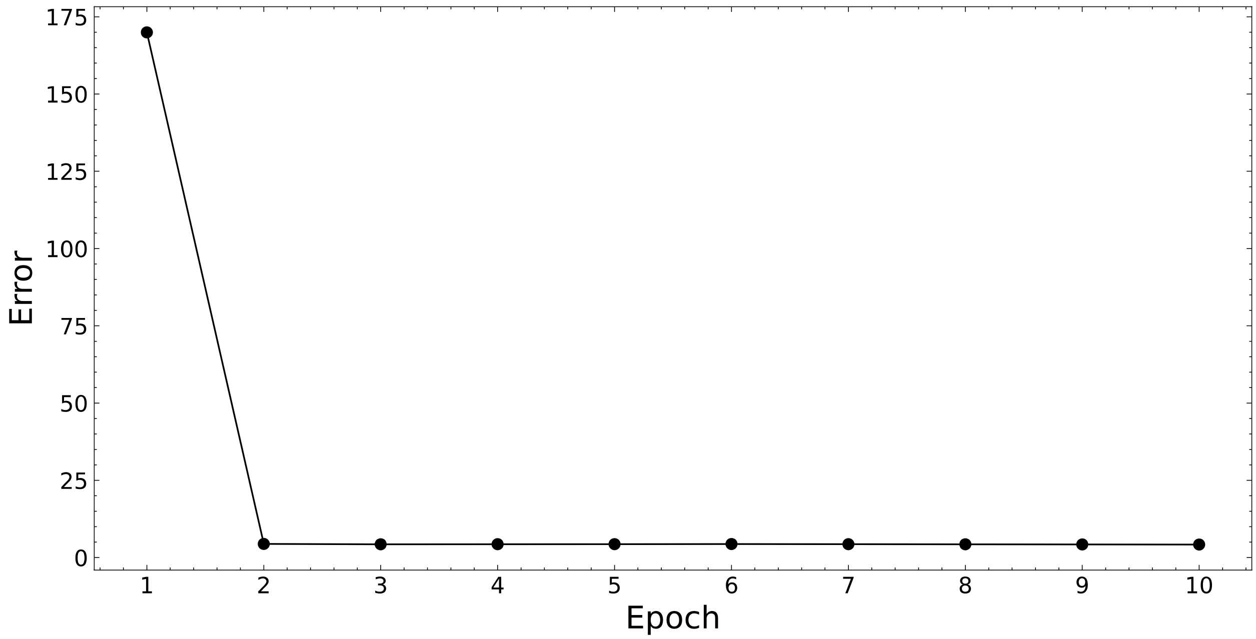

Fig. 6. Validation error of SSA-PNN. The plot shows the experimental results of the validation set with 10 epochs. The best validation performance was attained at epoch 2.

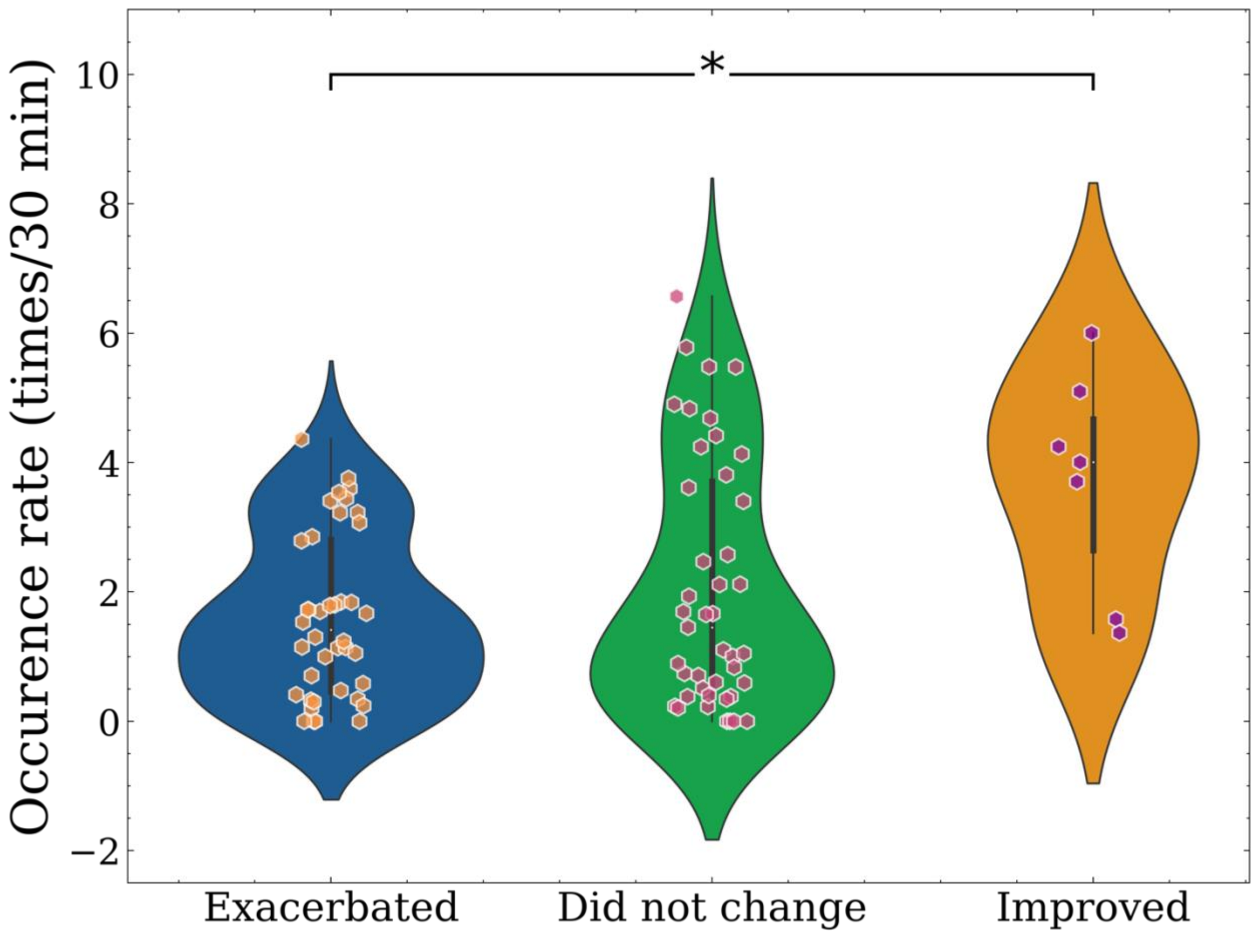

Fig. 7. Differences in occurrence rate of motif at three LBP conditions. The occurrence rate was higher in the improved group compared to the other two groups. $*p < 0.05$.

10. Tables

Table 1. Demographic characteristics

Subject (n)	22
Total sample size, days	90
Sample size (each subject), days	4.1 ± 3.6
Gender (male), %	50.0
Age, year	43.4 ± 8.4
Weight, kg	65.1 ± 10.0
Sitting, hour	5.6 ± 1.9
Motif[a], frequency/30min	2.0 ± 1.7
Level of sleepiness (score from 0-10)	6.6 ± 2.0
Level of fullness after breakfast (score from 0-10)	4.3 ± 3.6
E[b], n of subjects, %	13.6
NC[c], n of subjects, %	36.6
IM[d], n of subjects, %	0
Mixed up different change	50.0
E and IM[e], n of subjects, %	0%
E and NC[f], n of subjects, %	27.3
E and NC and IM[g], n of subjects, %	22.7

[a]The common motif identified in this study. [b]In recorded days, how many subjects LBP exacerbated. [c]In recorded days, how many subjects LBP level did not change. [d]In recorded days, how many subjects LBP level improved.
[e]In recorded days, how many subjects LBP exacerbated and improved.
[f]In recorded days, how many subjects, LBP exacerbated, did not change.
[g]In recorded days, how many subjects LBP exacerbated, did not change and improved.
E: LBP exacerbated
NC: LBP level did not change
IM: LBP level improved

Table 2. Characteristics by the change of LBP in each subject

	E (n = 3)	NC (n = 8)	E and NC (n = 6)	E, NC and IM (n = 5)
Sitting, hour	5.7 ± 1.6	4.9 ± 1.8	6.6 ± 1.7	5.0 ± 1.8
Motif, times/30 min	1.6 ± 0.3	2.1 ± 1.7	1.6 ± 1.3	2.4 ± 2.1
Sleepy (score from 0-10)	6.7 ± 2.4	7.8 ± 2.0	5.8 ± 1.6	6.3 ± 1.6
Breakfast (score from 0-10)	8.7 ± 0.5	6.7 ± 3.1	2.3 ± 3.3	3.8 ± 2.9

E: LBP exacerbated
NC: LBP level did not change
IM: LBP level improved

Table 3. Characteristics by the change of LBP in each day from all subjects

	E (n of event = 40)[a]	NC (n of event = 43)[b]	IM (n of event = 7)[c]
Sitting, hour	6.2 ± 1.8	5.1 ± 1.8	5.1 ± 2.4
Motif, frequency/30 min	1.6 ± 1.3	2.1 ± 1.9	3.7 ± 1.6
Sleepiness (score from 0-10)	6.2 ± 1.6	6.9 ± 2.2	6.3 ± 1.5
Fullness (score from 0-10)	3.5 ± 3.6	5.4 ± 3.5	2.1 ± 2.0

[a]In all the 22 subjects, there were 40 days that their LBP exacerbated.

[b]In all the 22 subjects, there were 43 days that their LBP level did not change.

[c]In all the 22 subjects, there were 7 days that their LBP level improved.

E: LBP exacerbated

NC: LBP level did not change

IM: LBP level improved

Table 4. The BIC values corresponding to each K values (window size = 5, β = 50, λ = 0.001)

K	4	5	6	7	8	9	10
BIC for states ($\times 10^5$)	12.3	12.7	13.6	13.2	13.3	12.8	12.7
BIC for motifs ($\times 10^5$)	5.5	8.3	8.1	7.9	8.9	8.4	8.7

BIC: Bayesian Information Criterion

Table 5. Classification performance comparison

Model	Accuracy (%)	Recall (%)	Precision (%)	F1 (%)
SSA-PNN	59.1	41.3	77.6	63.0
Extreme Gradient Boosting	58.3	43.7	61.6	60.1
Gradient Boosting Classifier	57.7	44.0	58.6	59.1
K Neighbors Classifier	57.4	43.0	54.5	60.0
Random Forest Classifier	57.0	43.4	51.6	59.3
Ada Boost Classifier	57.0	42.3	55.6	59.6
Ridge Classifier	56.7	39.7	69.0	59.2
SVM – Linear Kernel	56.5	44.3	52.0	57.9
Linear Discriminant Analysis	56.2	41.3	50.0	58.5
Logistic Regression	55.4	43.4	52.4	56.7

A comparison of the predictive performance of my model with other 9 commonly used models with 6-fold cross-validation 200 times.

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