A Functional PCA Model for the Study of Time Series of Pressure Maps

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Principal component analysis and functional regression are combined in a model to analyze a time series of pressure maps. The model is tested measuring the pressures over a chair seat while a subject performs a combination of simple movements. A sampling rate of 3 Hz is adequate for applying the model in sitting postures. The model is able to detect patterns of movement over time, although more variables are necessary if the movements produce similar pressure distributions.

Keywords: PCA, pressure maps, sitting posture, functional regression

The analysis of pressure maps is a common tool used in the quantification of postural behavior while sitting. The analysis of pressure maps has been used in different areas such as postural rehabilitation, ergonomic design, or the prevention of pressure ulcers. Pressure maps provide more information and they are as reliable as other techniques such as force platforms. Pressure data from experimental studies are temporal and spatial functions, rather than single values. Some researchers have dealt with the functional nature of pressure data by formulating topological models of the maps. Others have preferred to extract scalar data or characteristic parameters such as peak maximum pressures, contact surfaces, or weight indexes. However, these approaches do not use all the information included in the temporal function. Instead of extracting discrete parameters from temporal functions, it is possible to analyze the complete function using functional data analysis (FDA). Therefore, the object of analysis is not scalar data or characteristic parameters of the functions, but the functions themselves, and functional data in the form of vectors and matrices need not be simplified. The FDA technique applies methods of multivariate statistics, such as principal component analysis (PCA) or regression analysis (RA), but works with the whole function as data.

PCA has been used successfully to identify pressure patterns and clustering and is almost always a superior classification algorithm for pressure maps. However, we have not found evidence that this methodology has been used for assessing the temporal evolution of pressure maps. This paper uses a model that combines PCA and functional regression. We use PCA to classify pressure patterns, and functional regression to establish the activation of the patterns over time.

The aim of this study is to establish the capability of the PCA to express the temporal variations of a pressure map. Therefore, the objective is to demonstrate that each principal component into which the pressure data are broken represents a simple “movement” or variation of the pressure map.

However, to use the model, we must first establish the sampling frequency that avoids aliasing effects. High sampling frequencies avoid aliasing problems, but increase the size of the data and the time needed for PCA calculations.

The experiment was divided in two parts. The first part determines the most suitable sample frequency by means of Fourier analysis. The second part shows that the model can identify previously defined pressure patterns.

Methods

Instrumentation

The pressure recording system consists of a pressure-sensing mat with 36 x 36 pressure sensors matrix (X-Sensor Medical 4.2) connected to a computer through a signal acquisition unit. The X-Sensor software records the pressure maps—including the values of the 1296 sensors at each sampling instant. Accordingly, the
output file is a three-dimensional matrix in which the two first dimensions correspond to the 36 × 36 positions (x-y coordinates) and the third dimension corresponds to time.

**Model**

The model is explained in the following equation

\[ P(x, y, t) = P_{av}(x, y) + \sum_{i=1}^{nc} C_i \cdot P_i(x, y) + \text{error}(x, y, t) \]  

(1)

where

- \( x, y \) are the center of the sensor position; \( x \) is frontal plane, and \( y \) the sagittal plane
- \( P(x, y, t) \) is the pressure in x-y coordinates at time \( t \)
- \( P_{av}(x, y) \) is the average pressure in x-y coordinates
- \( P_i(x, y) \) is the principal component number \( i \)
- \( nc \) is the number of principal components included in the model
- \( C_i(t) \) is the temporal coefficient of \( P_i \)

To reduce the dependence of the data on the participant’s weight, the pressure maps are dimensionless. For that purpose, the average pressure map is calculated and each measurement of the individual (temporal) pressure map is divided by the weight (sum of the values of the average map).

The principal components are calculated using the MATLAB function PRINCOMP. To achieve this, each individual map is reshaped to a vector given that the PRINCOMP algorithm takes each row as an “observation.” For example, 1 minute measurements at 1 Hz will produce a matrix of 36 × 36 × 60 (x-y-time). The reshaping process creates a matrix of 60 × 1296 (1296-time). The PRINCOMP algorithm provides a matrix including all the principal components and the eigenvalues, and which are proportional to the variance explained by each principal component.

The percentage of variance explained by the \( i \)-th component is calculated with the following equation:

\[ \text{Var}_i = 100 \cdot \frac{\text{Eigenval}_i}{\sum \text{Eigenval}} \]  

(2)

The accumulated variance at the \( i \)-th component is

\[ \text{Varacum}_i = 100 \cdot \sum_{j=1}^{i} \text{Var}_j \]  

(3)

We include in the model the principal components that explain 90% of variance (Varacum ≥ 90).

**Experimental Setup**

**for Frequency Analysis**

The experiments were performed in the laboratory of the Institute of Biomechanics of Valencia. The laboratory simulates a typical office workplace: desk, chair, and computer. Eight subjects participated in the study with an age range from 24 to 28 years; a weight range from 60 to 78 kg; and a height range from 165 to 174 cm. The participants sat on an office chair with a pressure-sensing mat. The chair height was adjusted to accommodate each subject’s height. Subjects were instructed to remain seated while they performed activities such as browsing the web or reading a book, with no instruction as to allowable motion leaning, or backrest.

The subjects participated in three consecutive tests. The order of the tests was randomized:

- Test 1: 10 minutes, sampling rate 10 Hz, 6000 maps.
- Test 2: 30 minutes, sampling rate 3 Hz, 5400 maps.
- Test 3: 2 hours, sampling rate 1 Hz, 7200 maps.

The reason for selecting these tests was to limit the size of the data to 7500 maps. We used a computer with 2 gigabytes of RAM and WINDOWS XP 32 bits. Previous trials showed that measurements with more than 7500 maps (36 × 36 × 7500 double precision) fail due to memory limitations.

The power spectral density (PSD) function was applied to determine the upper frequency limit. The upper limit criterion is the frequency that reaches 90% of the PSD in the movement of the center of pressures (CoP), and the CoP is used because is a reliable parameter and its use makes it possible to compare the results with previous research in the literature.

**Experimental Setup**

**for Checking the Model**

One person (24 years, 70 kg) sat on an office chair equipped with the pressure-sensing mat. The sampling rate was 3 Hz (3 maps per second), based on the results of the frequency analysis.

The first part of the analysis consisted of the PCA of the files with pressures maps when the subject makes one simple movement. The subject performed six simple movements, whose corresponding temporary pressures maps were recorded in independent files. The subject was instructed about the range of movement of the trunk. Movements were repeated (5 s per repetition) for a duration of 1 minute and then saved in a separate file. This was repeated for all movements:

- **Mov1**: Trunk swinging on the sagittal plane with pelvis rotation. The participant tilted the trunk successively forward and backward to the backrest (15–20° rotation about a horizontal axis oriented medio-lateral).
- **Mov2**: Lateral trunk swinging. Right and left alternating inclination of the trunk on the frontal plane (15–20° rotation about a horizontal axis oriented anteior–posterior).
- **Mov3**: Lean on the chair arm. The participant pushed on the chair arm for 2 s, leaning on it, and then released the weight back to the buttocks.
Mov4: Support on the right/left foot. This action consisted of pushing on the floor with the right and left foot successively, releasing the pressure under the buttock corresponding to the same side.

Mov5: Gluteus contraction/relaxation. The participant contracted both gluteus muscles, to stiffen them, for a few seconds and then relaxed them.

Mov6: Legs adduction/abduction. This movement consisted of opening and closing the legs successively while sitting.

The first principal component is extracted from files 1–6. The hypothesis is that the first component is representative of the simple movement. We will refer to the movements as Mov1, Mov2, and so on. Each of these first components is a pressure map. Then, we have 6 pressure maps that identify the 6 simple movements.

Subsequently, the previously defined movements were repeated sequentially during three minutes (30 s per movement series), so that the seventh recorded pressure file contained the 6 aforementioned movements. The order of the movements is known to check whether the model is able to identify the movements along the time.

From file 7, we extracted the components that explain 90% of the variance. The components are classified and selected by means of a cross-correlation with the first principal component corresponding to simple movements (Mov1 to Mov6). We then calculated the temporal coefficients $C(t)$ of the model by linear regression.

**Results**

The PSD analysis probes that 3 Hz sampling rate is adequate. And higher frequencies are not necessary. The CoP movement on two axes (x,y) shows that the frequency limit of 90% PSD ($F_{90}$) increases from the 1 Hz to 3 Hz sampling rate. The average value of $F_{90,x}$ for the 1 Hz sampling rate is 0.02 Hz, and $F_{90,y}$ is 0.01 Hz. The average value of $F_{90,x}$ for the 3 Hz sampling rate is 0.11 Hz, and $F_{90,y}$ is 0.02 Hz. The differences between 1 Hz and 3 Hz are statistically significant ($t$ test with $P$-value < .05). The average value of $F_{90,x}$ for the 10 Hz sampling rate is 0.16 Hz, and $F_{90,y}$ is 0.02 Hz. The differences between 3 Hz and 10 Hz are not statistically significant ($t$ test with $P$-value > .05). The range of frequency content does not change from the 3 Hz to 10 Hz sampling rates. For this reason, the sampling frequency selected for checking the model is 3 Hz.

One component is enough to represent a simple movement. The PCA of the simple movements shows that the 1st component explains more than 90% of the variability in all the cases. For this reason, 1st components are a good representation of the movements. Each of these 1st components is a pressure map. Then, we have 6 pressure maps that identify the 6 simple movements.

The combined movement (six movements) has five principal components that explain 90% of the variance (Table 1).

The principal components are classified by means of the maximum coefficient of correlation with the first principal component of the simple movements (Table 2). Then Mov1 correlates with C3, Mov2 correlates with C2, Mov3 correlates with C1, and Mov5 correlates with C4. C5 has correlation values that are too low to be classified. Component 5 (C5) has low relation with the movements (correlation < 0.5). For this reason, we do not use C5 in the model.

The correlation can be visualized by comparing the pressure maps of the 1st component of the simple movement and the principal component with the highest correlation (Figure 1).

<table>
<thead>
<tr>
<th>Table 1</th>
<th>Accumulated variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Component</td>
<td>C1</td>
</tr>
<tr>
<td>Variation explained</td>
<td>52%</td>
</tr>
<tr>
<td>Accumulated variance</td>
<td>52%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 2</th>
<th>Cross-correlation values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simple Movements</td>
<td>Principal Components of the Multiple Movements File</td>
</tr>
<tr>
<td>Mov1</td>
<td>Forward/backward trunk swinging</td>
</tr>
<tr>
<td>0.72</td>
<td>0.38</td>
</tr>
<tr>
<td>Mov2</td>
<td>Right/left trunk swinging</td>
</tr>
<tr>
<td>Mov3</td>
<td>Push/release on chair arm</td>
</tr>
<tr>
<td>Mov4</td>
<td>Right/left foot support</td>
</tr>
<tr>
<td>Mov5</td>
<td>Muscular contraction</td>
</tr>
<tr>
<td>Mov6</td>
<td>Thighs abd/adduction</td>
</tr>
</tbody>
</table>
The temporal evolutions of the dimensionless coefficients of the model indicate the activation of the simple movements (Figure 2). The vertical labels of the graphs indicate the component and the correlated movement. For example “Mov1 - C3” is the temporal coefficient of the component 3, and this component has the highest correlation with the movement 1 (Mov1). The vertical lines indicate the approximate time when the subject changes the movement. According to the graphs in Figure 2, the third component (C3), which is correlated with the first movement (forward/backward trunk swinging), has its maximum activity during the time interval corresponding to that individual movement. The second component (C2), which is strongly correlated to the second movement...
(lateral trunk swinging), presents its maximum amplitude during the time interval corresponding to that second movement, and is also present in the time interval corresponding to the fourth movement (alternating support on right/left foot). The first component (C1), which was correlated to the third movement (push-release on the chair arm), is present at the time interval corresponding to the third movement, and the fourth movement (with lower amplitude). The third principal component (C3), which was associated to the first individual movement (forward/backward trunk swinging), has its maximum values during the time interval corresponding to that individual movement. The fourth component (C4), which is correlated to the fifth movement (contraction/relaxation of the gluteus musculature), has a greater presence during the time interval corresponding to that fifth movement.

**Discussion**

The frequency analysis demonstrates that a sampling rate of 3 maps per second (3 Hz) is adequate for measuring pressure distributions in sitting movements. This result is similar to the results of Genthon et al.\(^1\)

We can relate components with movements by means of correlation and time activation. The highest correlation indicates the movement more related with the component. The PCA analysis shows that movements 1, 2, 3, and 5 are related with one principal component: Mov1 and C3, Mov2 and C2, Mov3 and C1, Mov5 and C4. This correspondence is clearly seen in the time graphics (Figure 2) and pressure graphics (Figure 1). However, the component can have relation with other movements because the model distinguishes movements if they produce a different pressure distribution. This could explain the correlation of Mov1 and C1.

There is not a principal component of the multiple movement file that correlates with the fourth movement (lateral load transfer by supporting alternatively on the left and right foot). C2 and C1 shows activity when Mov4 happens (Figure 2). This movement is explained simultaneously by component C2 that describes the effect of the right/left trunk swinging, and C1 that describes the pushes on the chair arm.

The fourth movement consists of alternating support on the right/left foot, so that support is partially composed of an increase and decrease in the total weight on the chair. However, the third movement also produces an increase and decrease in the weight. At the same time, the fourth movement produces a lateral load transfer by alternatively supporting with the left and right foot; and the second movement (lateral trunk swinging) also has this partial effect. This could be why the fourth movement is a mix of C1 and C2.

Although 5 principal components were selected to explain 90% of the variability, C5 describes the least variability of all the principal components. Due to explain the least variability and lack of an additional distinct from all other movements, C5 does not show a clear relation to any of the simple movements.

The sixth movement does not correspond with a principal component. This movement consists of the abduction-adduction of the thighs, and produces less change in the pressure distribution than the other movements. The effect on pressure is not enough to be detected.

The model we propose can decompose a temporal series of pressure maps into components. And these components are clearly related with a simple pattern of movements. Moreover, the model detects the changing patterns over time. The model can distinguish pattern of movements if they produce a different pressure distribution and this is useful for analyzing a time series of pressure maps. However, it would be necessary to add other variables to the model to detect patterns with similar pressure distributions over the seat. Perhaps variables such as the pressure over the backrest or the armrests. The model has been verified versus simple movements measured with one subject. Other people could have different simple movements. Future work is necessary to verify the model with more people and check the necessity of calibrating each subject. One possible application of this methodology is to identify patterns of healthy people. Perhaps the healthy patterns...
could be applied in pressure relief cushions to prevent pressure sores.

Summarizing, the application of PCA and the functional regression method is a useful tool for analyzing the time patterns of pressures maps. Although this mathematical method is not novel, there is no evidence in the literature of this application.

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