Feature Extraction and Expertise Analysis of Pianists' Motion-Captured Finger Gestures

Mickaël Tits, Joëlle Tilmanne, Nicolas d'Alessandro

Numediart Institute, University of Mons, Belgium

{firstname}.{lastname}@umons.ac.be

Marcelo M. Wanderley

Centre for Interdisciplinary Research in Music Media and Technology, McGill University, Montreal, Canada marcelo.wanderley@mcgill.ca

ABSTRACT

This paper investigates the analysis of expert piano playing gestures. It aims to extract quantitative and objective features to represent pianists' hands gestures, and more specifically to enable characterization of the expertise level of pianists. To do so, four pianists with different expertise levels were recorded with a marker-based optical motion capture system while playing six different piano pieces. Movements were decomposed with principal component analysis, leading to uncorrelated subparts called eigenmovements. We observed that four eigenmovements allowed representation of the original movement with 80% accuracy, and less than ten eigenmovements were sufficient to represent it with 95% accuracy. The eigenvalues, representing the contribution of each eigenmovement in the original movement, allowed comparison of pianists with each other, and showed that more trained pianists seemed to use more eigenmovements, reflecting a better motor control of their hands.

1. INTRODUCTION

The recent development of motion capture (MoCap) technologies has enabled very accurate measure and analysis of movements in many research areas. In the context of the study of music performance, very complex gestures, including pianists' hands and finger gestures, could be captured with a submillimeter accuracy [1].

The hand is a complex body limb, endowed with 23 Degrees Of Freedom (DOF), and its operation depends on muscles, articulations, and neurons, allowing for a great range of movements. Various papers, in the biomechanics field of study, investigate hand motor control. Despite the complexity of the hand structure, it can be easily controlled thanks to different enslaving effects restricting its movements, including intertendinous connections, muscles synergies, and neuroplasticity [2]. These effects facilitate the coordination between the movements of different DOF in simple tasks like prehension,

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but also lead to a reduction of the effective number of DOF of a hand. This can be restricting for complex motor activities like piano playing [3]. However, intensive training can lead a pianist to increase the motor control of his hands by forcing a reprogramming of the motor cortex (neuroplasticity), allowing him to make more easily and accurately complex movements, and thus reach more virtuosity [4].

Several papers investigate the motor control of pianists. The first study in this context was achieved in 1930 by Bernstein and Popova [5], concerning the "biodynamics of the piano strike". They analyzed the dynamics of shoulder, elbow and wrist joints, during series of octave strikes executed at different tempi, and described how the segmentation and coupling of movements varied with the tempo. More recent papers, inspired by Bernstein's approach, studied the dynamics of the fingers according to the tempo on a simple note progression exercise [6], distinct inter-joints coordination on alternate keystrokes of two fingers [7], timing accuracy according to tempo and key velocity [8], or finger and hand movements efficiency and temporal control in fast performance [9].

These studies focused on the analysis of a specific feature of the movement, based on one simple single-handed piano exercise, limiting the possibilities of interpretations of the results. In this paper, we focused on a more general approach, Principal Component Analysis (PCA), allowing analysis of real complex piano pieces. PCA allows decomposition of data sequences in several uncorrelated components, and evaluation of the minimum number of components required to represent the whole data sequence. PCA is widely used in motion analysis. As an example, PCA was used to decompose and analyze full-body movements, like human gait [10], or dance movements [11]. In the field of neuroscience, PCA has already been used on finger gestures to analyze dependencies between finger movements due to muscles synergies [12, 13]. In the context of the study of music performance, we decomposed pianists' finger gestures with PCA, allowing us to evaluate the minimum number of components required to represent the whole gesture of a hand, thus reflecting the complexity of the movement.

2. METHODS

2.1 Database

The study was based on four pianists (2 females, 2 males, age 22.5 ± 5.5 , years of training 15 ± 6). According to their level of training, each pianist played different excerpts of the six following pieces: Bagatelle No. 25 in A minor (Ludwig van Beethoven), Prelude and Fugue in C Major (Johann Sebastian Bach), Fantasy in C Major (Robert Schumann), Comptine d'un autre été (Yann Tiersen), The Promise (Michael Nyman), and Struggle for Pleasure (Wim Mertens). These pieces were chosen as they are well-known, and for their own particularities and difficulties for both hands, providing a large variety of gestures.

The collection of a multimodal database was achieved with a marker-based optical motion capture system (Qualisys 1), and a keyboard (Yamaha™ CP300). The motion capture system, equipped with 12 infrared cameras, was used to record the 3D trajectories (or MoCap data) of 27 reflective markers placed on each articulation of the hands, allowing accurate capture of all DOF. All the sequences were recorded with a frame rate of 100 FPS. Additionally, The keyboard was used to record MIDI data. The MIDI protocol allows transmission of a message for each key press and release, providing information about the note, timestamp and velocity of the pressed key. MIDI data thus represent the score played by the pianist and can be used as temporal landmark for the analysis of MoCap data. An example of 3D rendering of the motion capture data can be seen in this video: https://youtu.be/lNwWHlkjNJ4.

2.2 Procedures

The multimodal database was analyzed using the MoCap Toolbox ², and the Midi Toolbox ³. In this work, MIDI data were used for alignment and segmentation purpose only. In order to have comparable data between the pianists, the MIDI scores were used to segment similar passages of the pieces excerpts for each pianist. In parallel, to analyze relevant Mo-Cap data of hand gestures, we extracted markers trajectories of each hand, and translated the reference coordinate system, originally placed on the keyboard, onto a marker placed on the wrist. The analyzed trajectories were hence relative to the wrist, and corresponded to the DOF of the hand only. For each hand, a subset of MoCap data was thus extracted, corresponding to 3D trajectories of 26 markers. These data were then processed with PCA. PCA allowed decomposition of the gestures of each hand in uncorrelated subparts, called eigenmovements [11], corresponding to the Principal Components (PCs). Each PC is indexed with its eigenvalue, reflecting its weight in the whole gesture.

3. RESULTS AND DISCUSSION

From PCA, two main results could be analyzed: the decomposition of hands gestures in eigenmovements (Section 3.1), and cumulative eigenvalues ratios, used for comparison between sequences and pianists (Section 3.2).

3.1 Eigenmovements Decomposition

All the MoCap sequences were processed through PCA, allowing decomposition of the gestures in eigenmovements. Fig. 1 shows the first eight eigenmovements ⁴ of pianist #1's right hand on the chorus excerpt of Tiersen. Traces of each marker (in red) allow visualization of the movements corresponding to these eigenmovements (see https://youtu.be/6qIHn9UUJW4 for video version). The eigenvalues ratios ⁵ of these eigenmovements, reflecting their respective weights in the whole gesture, are shown in Fig. 2.

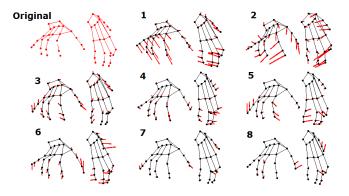


Figure 1: Original movement and first eight eigenmovements - Pianist #1 - Right hand - Tiersen chorus

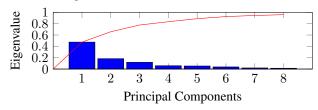


Figure 2: Eigenvalues ratios of the first principal components - Pianist #1 - Right hand - Tiersen chorus

For instance, the first eigenmovement, representing 47% of the original gesture, corresponds to the inclination of the hand. The fingers and the palm are indeed going up and down relative to the wrist, throughout the excerpt. These up-down movements are also respectively coupled with slight right-left movements.

According to the patterns used for a given piece, hand movements may be very different from one piece to another, and hence the first eigenmovements may be different for several

¹ Qualisys: www.qualisys.com

² MoCap Toolbox: https://www.jyu.fi/hum/laitokset/musiikki/en/research/coe/materials/mocaptoolbox

³ Midi Toolbox: https://www.jyu.fi/hum/laitokset/musiikki/en/research/coe/materials/miditoolbox/

 $^{^4}$ The number of eigenmovements to show was arbitrarily chosen so that they represent at least 95% of the whole gesture.

⁵ The eigenvalue ratio is the eigenvalue divided by the sum of all eigenvalues of each component, so that the sum of all eigenvalue ratios gives 1, i.e. 100% information of the whole gesture.

pieces. Eigenmovements were therefore computed separately for each MoCap sequence. All of them represented a relevant and tangible subpart of the whole movement, allowing comparison for different pianists and pieces. The first eigenmovements were generally similar for different pieces. The first three to five eigenmovements generally corresponded to global movements of the hand, involving coupled up-down, left-right, opening-closing movements of the hand. The pronation - supination of the forearm 6 was often corresponding to eigenmovements #4, #5 or #6 according to the piece and the pianist. Eigenmovements #6 to #8 generally corresponded to movements involving one, two or three fingers, more dependent to the particular piece.

From these observation, we can say that the PCA process allowed extraction of relevant quantitative and objective features, allowing analysis and comparison of pianists and piano pieces. Eigenmovements are an interesting way to decompose the movement, and could be seen as effective DOF of the hand. Other methods such as Independent Component Analysis [14] or Empirical Mode Decomposition [15] could be investigated to obtain different eigenmovements, and compare their efficiency for gesture decomposition.

3.2 Cumulative Eigenvalue Ratios

This Section presents the use of Cumulative Eigenvalues Ratios (CER) for comparison between pieces sand pianists. The red curve (see Fig. 2) shows the cumulative sum of the eigenvalues ratios, representing the information accumulated by the first components. We can see that the first eight eigenvalues are sufficient to represent the whole gesture with an accuracy of 95%. The first part of the curve has a high gradient, showing the importance of the first components. The first three components indeed represent already 77.6% of the movement.

These CER were extracted separately for each hand on each sequence, and allowed comparison between pieces and pianists. On Beethoven, the left hand only produces simple arpeggios with three fingers, while the right hand produces a more complex melody with five fingers. We can see in Fig. 3 (left) that the CER are generally higher for the left hand, for the three pianists that played the excerpt, meaning that less eigenmovements are needed to represent the gesture. On the other side, on Tiersen, left hand patterns are more complicated, resulting in lower CER (see Fig. 3 (right)).

A general observation of all the sequences of the four pianists on six excerpts showed that CER seem to depend on the complexity of patterns of each hand on the excerpt, and on the pianist. For a same piece, more trained pianists seemed to have generally lower CER, meaning that they used more eigenmovements. In order to compare pianists regardless of the played piece, we concatenated the sequences of the different excerpts, and analysed them through PCA to obtain CER

more independent of the excerpt for each pianist (see Fig. 4). For the three pianists ⁷, eight to ten eigenmovements are generally needed to provide 95% information on the movement, except for pianist #1's left hand, for which six eigenmovements are sufficient. In order to understand that difference, each pianist was asked about his training and repertoire. Pianists #3 and #4 followed an intensive academic training and generally practiced classical music. On the other hand, pianist #1 was a more occasional pianist and generally played more modern pieces, like piano adaptations of popular tunes.

All these results seem to show that from the 23 DOF of the hand, the number of effective components of the movement is generally much less, in the specific case of piano playing. Comparison of the CER of each pianist on each excerpt seemed to show that more trained pianists had generally lower CER, and thus used more various eigenmovements. However, this observation is preliminary, and limited by the small number of participants. Nonetheless, this method allowed a first interpretation, linking the variety of eigenmovements in a gesture with the motor control of the hands, or expertise, in piano playing.

From a different perspective, the process of dimensionality reduction with PCA showed that the pianist's expert gestures can be represented with a few PCs, or eigenmovements. In the context of the design of new musical instruments, these components could be used to virtually recreate a reduced model of the hand, and use this model as a controller for the synthesis of new sounds.

4. CONCLUSIONS

This paper investigated feature extraction of pianists' finger gestures on real piano pieces, using optical motion capture and principal component analysis. To achieve this goal, a database was collected with four pianists playing different piano pieces. Along with MoCap data captured with the Qualisys motion capture system, MIDI data were recorded and were used as annotations of MoCap data. PCA was performed on each data sequence, and allowed extraction of different features: eigenmovements and eigenvalues ratios. Preliminary results showed that eigenmovements were tangible and relevant subparts of the whole hand gesture on piano, and eigenvalues ratios seemed to be related to the complexity of the movement, reflecting the difficulty of the piece and the expertise of the pianist. The method seems promising, though further investigation should be done with a broader database, in order to obtain more significant results and conclusions.

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⁶ The pronation-supination of the forearm induces rotation of the hand around the axis going through the forearm, and is therefore considered as a movement of the hand itself. This movement was often coupled with alternate flexion-extension of the thumb and the pinkie, as the purpose of both movements is similar, that is alternate keystrokes of extreme fingers.

⁷ The most novice of the four pianists played only one piece and could not be taken into account for this analysis.

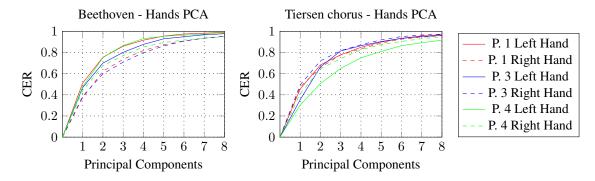


Figure 3: CER for pianists #1, #3 and #4 on Beethoven (left) and Tiersen chorus (right)

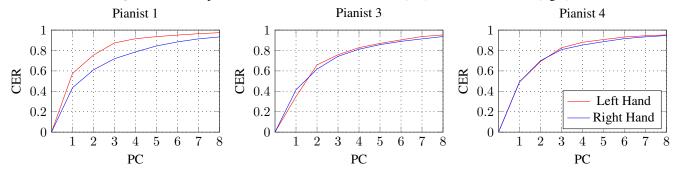


Figure 4: CER for pianists #1, #3 and #4 - Concatenation of four excerpts: Tiersen chorus and verse, Beethoven, and Bach

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