PERSONAL IDENTIFIERS IN MUSICIANS' FINGER MOVEMENT DYNAMICS

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INTRODUCTION

Famous musicians (e.g. Vladimir Horowitz) strike us with their outstanding performances. However, how viewers recognize performers' unique musical *signatures* is little understood.

Most studies on automatic recognition of personal identity have been carried out using static biometric indicators such as photographs (e.g. faces) or fingerprints (Jain, Ross, & Pranhakar, 2004). However, dynamic indicators, such as gait, can also aid to identify individuals (Bobick & Davis, 2001).

Movement dynamics in music performance, among the fastest sequences produced by humans, may carry information that uniquely identifies persons.

Goal

Assess whether pianists' finger movements are characterized by dynamic landmarks that uniquely identify musician and finger

GENERAL METHOD

Participants 4 skilled pianists (mean age = 24.3 years) with an average of 16.3 years of piano performing experience from the Columbus, Ohio, music community

Material 2 novel simple melodies (13 quarter notes), with limited horizontal hand displacement and no "thumb-under" movement

Procedure

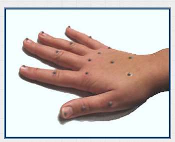
Participants memorized each melody and performed them from memory, following the tempo indicated on a metronome. Five experimental tempi ranged from slow (60 beats/min; beat = quarter note) to fast (245 beats/min).

Each pianist performed each melody at least twice at each tempo. Only error-free performances were analyzed totaling 45 performances.

Apparatus

Melodies were performed on a Roland RD600 digital piano (1-ms time resolution). Fingers movement during performance was recorded by a Vicon-8 motion capture system (sampling frequency: 120 Hz; spatial resolution: .01 mm).

Passive 3-mm markers were glued to the fingernails at several locations of the right hand. Fourteen cameras with fine lenses, located around the pianist, captured markers' movement. Additional markers were placed on the finger joints and on the front surface of the piano keys to monitor key movement during performance.



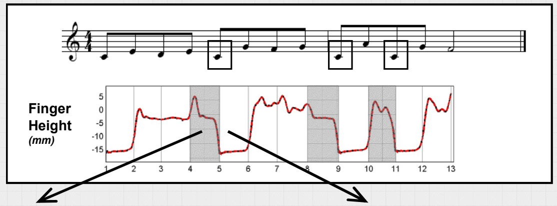
Analyses

Movement data in the vertical plane (perpendicular to the piano keyboard) from the fingertip markers were analyzed relative to the piano key movements. This accounted for how fast (loud) keys are struck.

Using Functional Data Analysis (FDA, Ramsey & Silverman, 2005) movement velocity and acceleration were computed as continuous functions starting from discrete data. Velocity and acceleration curves were smoothed with order-6 splines as basis functions in the FDA with a penalty function (lambda) between 10^{-12} and 10^{-13}.

1. How can we define a musical signature?

Finger motion in the vertical plane revealed **systematic markers before and after each keypress**.

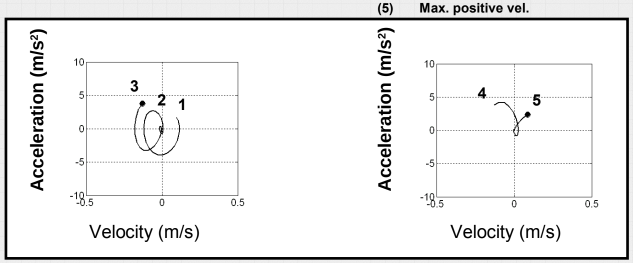


***Signature* BEFORE keypress**

(1) Maximum positive velocity
(2) Plateau around 0 vel. / 0 accel.
(3) Max. negative vel. and positive accel.

***Signature* AFTER KEYPRESS**

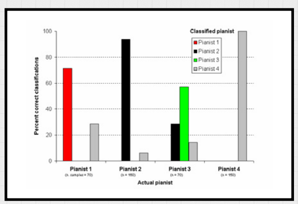
(4) Maximum negative velocity and positive accel.
(5) Max. positive vel.



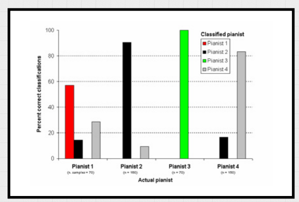
2. Can we classify pianists based on movement dynamics?

The portion of the velocity- acceleration curves before and after keypresses that differed among pianists, as assessed through Functional Anova (Ramsey & Silverman, 2005) was entered in a Principal Component Analysis. The first 5 principal components (accounting for at least 95% of the variance) from velocity and acceleration were used to train a 2-hidden-layer neuronal network with resilient back-propagation algorithm (total number of samples = 450; the n. of samples per pianist is indicated below) in order to classify pianists. Pianists' classification was performed separately for each finger, and the results were combined to obtain the final classification rate. The network classification performance was optimized using bootstrap techniques (i.e. bagging) and tested using standard cross-validation methods.

BEFORE keypress
87% correct classifications



AFTER keypress
84% correct classifications



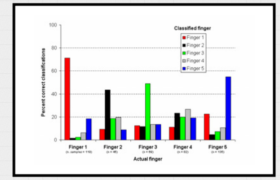
3. Can we classify fingers based on movement dynamics?

As with performer identification, finger classification of velocity-acceleration trajectories was based on movement before and after keypress.

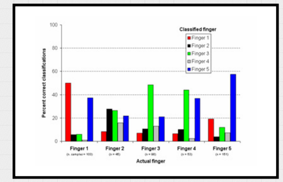
The 2-hidden-layer neuronal network was trained on 450 samples (the n. of samples per finger is reported in the graphs). Then the network performance was improved using bootstrap techniques and tested with cross-validation methods.

Fingers 1 and 5 were well-classified (59%). Differences between fingers may be related to fingers' degree of independence (i.e. enslaving; see Slobounov et al., 2002).

BEFORE keypress
53% correct classifications



AFTER keypress
45% correct classifications



CONCLUDING REMARKS

Pianists' finger movements during keypress contain identifiers unique to performers and fingers.

This is striking considering that 1) identification was achieved with very little information and 2) the pianists tested were not chosen *a priori* as having very different performance styles.

Subtle individual differences may ultimately contribute to the art of great performers.

Motion dynamic landmarks may be useful for modeling complex finger movements such as handwriting and sign language.

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