SmoothOperator : A Device for Characterizing Smoothness in Body Movement

Adrián Artacho*
Leonhard Horstmeyer*
adrian.artacho@gmail.com
horstmeyer@mdw.ac.at
University of Music and Performing Arts Vienna
Austria

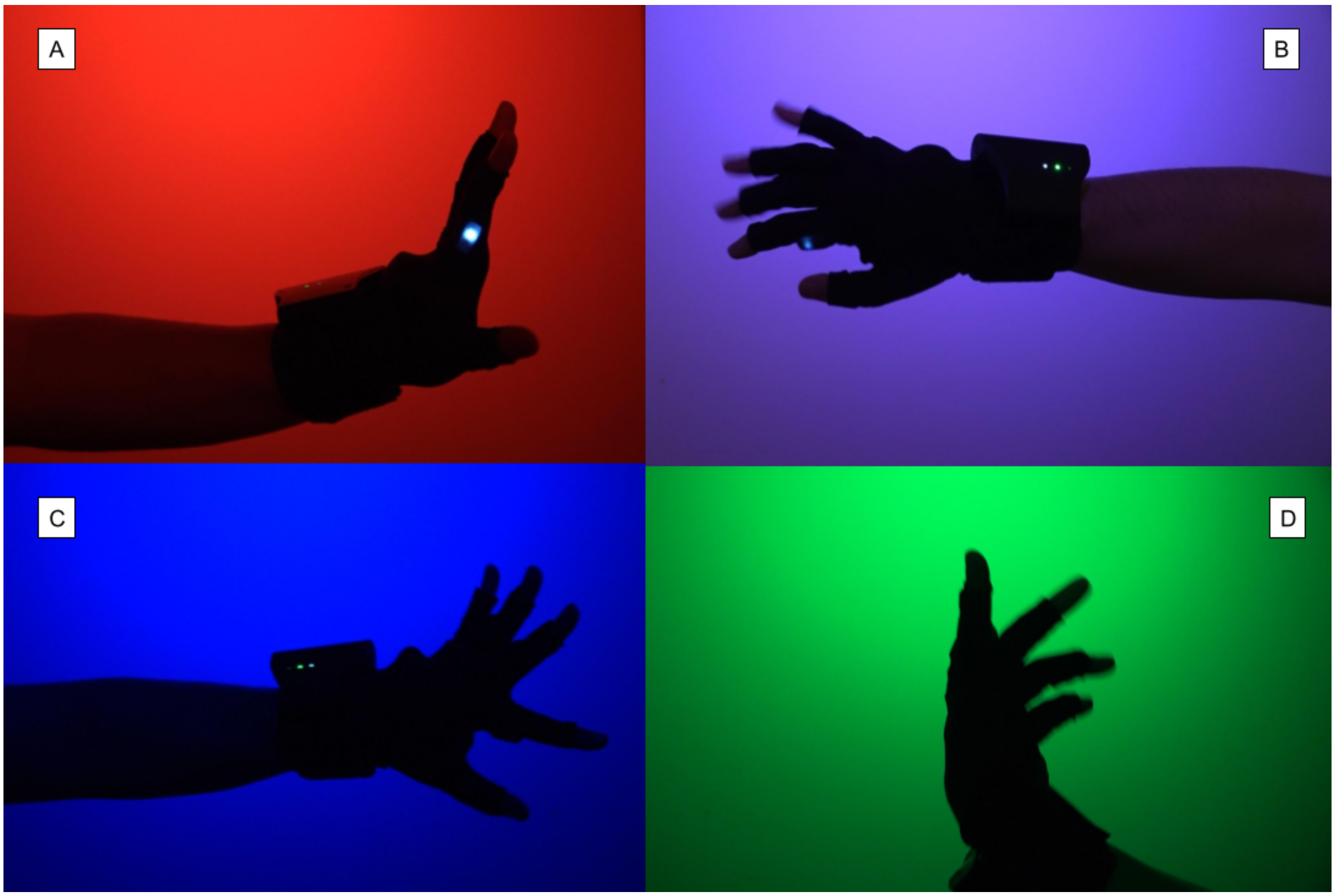

Figure 1: Stills from a practice session, where the stage lights convey movement quality according to smoothness profiles A-D, predetermined by the user. As a motion capture device we used the MiMU Glove.

ABSTRACT

In our research we faced the problem of characterizing smoothness in human movement. Even though 'smooth' is a common way to describe and conceptualize motion in the performing arts as well as in informal speech, we realized the need for a tool to differentiate between various degrees and modes of smoothness. We propose that smoothness operates at different interlocking orders. These appear only in aggregation, intertwined with other qualities of body movement. Akin to how a spectrometer splits light into a spectrum of frequencies, we developed a method to measure the

*Both authors contributed equally to this research.

MOCO'22, June 22–24, 2022, Chicago, IL, USA

ACM ISBN 978-1-4503-8716-3/22/06…$15.00
https://doi.org/10.1145/3537972.3538000

degree of smoothness in each order, as an epistemic tool for dance practitioners to investigate the quality of body movement from a fresh perspective. To this end we have implemented a device that provides dancers with aural, haptic and visual feedback in real time, taking into account the constraints of a dance practice session.

CCS CONCEPTS

• **Applied computing → Performing arts**; • **Human-centered computing → User interface toolkits**.

KEYWORDS

movement analysis, contemporary dance, smoothness, performance tool

ACM Reference Format:
Adrián Artacho and Leonhard Horstmeyer. 2022. SmoothOperator : A Device for Characterizing Smoothness in Body Movement. In *8th International Conference on Movement and Computing (MOCO'22), June 22–24, 2022, Chicago, IL, USA.* ACM, New York, NY, USA, 6 pages. https://doi.org/10.1145/3537972.3538000

1 INTRODUCTION

Smooth is a term used in a number of disciplines with rather diverse meanings to refer to the 'smoothness' quality of sometimes disparate processes. In music for instance, the term smooth has been used to describe a quality of certain chord progressions [6], a perceived quality of some melodic passages [10], as well as specific music related movement characteristics. In philosophy, Deleuze and Guattari's seminal work [9] notably introduced the notion of smoothness to signify the aspect of a phenomenon that covers its intensive and qualitative nature as opposed to the extensive and quantitative one. When referring to body movement, a general definition of 'smooth' states that [it] "is perceived to be smooth, when it happens in a continual fashion without any interruptions" [2]. Moreover, since smoothness in body movement is considered to be a revealing characteristic of health and neurological development [2], different measures of smoothness have been proposed over the years from the field of health and rehabilitation [13]. Some research has gone as far as to suggest a correlation between smooth speed profiles of movement and psychological states such as 'flow' [5]. In mathematics however, the notion of smoothness has a very specific meaning, which refers to the existence of derivatives in all orders. Thus a motion is considered to be smooth if there are no abrupt changes in the position, in the velocity, in the acceleration, in the *jerk* (rate of change of acceleration), and so on.

Smooth is also used in dance to loosely describe the perceived smoothness of movements, progressions, and transitions. However, there are very few tools that provide insight into its objective characteristics[1] beyond fields like rehabilitation [2] or robotics [12]. We would like to remedy this situation by providing an easy-to-use tool that can be utilized in as close an ecological setting as possible. Our contribution is to apply such metrics of movement smoothness to dance, and develop a device that can be playfully incorporated into dance practice as a tool to interrogate movement quality from a fresh perspective.

[1] Orlandi et al. state that Research in dance has traditionally 'rarely studied objective features like speed or acceleration' [11].

2 MEASURING SMOOTHNESS

The task of measuring smoothness of body movements typically revolves around tracking irregular abrupt signals using spectral methods [2] or tracking the variation of acceleration over time, the so-called *jerk*.[2] Our approach does not track isolated quantities by themselves, but instead acknowledges that all orders of derivatives are related to each other and therefore the characteristics of the motion are captured by their joined behavior. In the following we describe the spectral metric in contrast with our proposed approach of aggregated orders of smoothness.

2.1 Spectral approach

The spectral metric aimed at measuring smoothness was put forth by Balasubramainan et al. [1]. They introduced the spectral arc-length that uses a movement speed profile's Fourier magnitude spectrum to quantify movement smoothness. They start from the speed profile $v(t) := \frac{dQ}{dt}$ for some movement $Q(t)$. The Fourier-transformed value $\widetilde{v}(\omega)$ is then a spectral function of the frequency ω. The more modulated $\widetilde{v}(\omega)$ becomes, the less smooth the movement. This observation is at the heart of the authors' rationale to put forth the arc-length of the normalized curve $\widetilde{v}(\omega)/\widetilde{v}(0)$ up to a given spectral threshold ω_0:

$$\frac{1}{\omega_0}\int_0^{\omega_0}\sqrt{d\omega^2 + \frac{d\widetilde{v}(\omega)^2}{\widetilde{v}(0)^2}} \tag{1}$$

as a measure for smoothness, or rather non-smoothness. The Fourier transform is particularly good at picking up irregularities in repetitive patterns. Thus this metric will work very well to pick up a tremor or other secondary movement patterns with a higher frequency signature. It has, however, drawbacks for the analysis of movement in dance where modulations are not only common, but an important part of a dancer's movement palette.

2.2 Orders of Smoothness and Their Aggregation

It is an intriguing feature of the physical world that the way things change is not only subjected to change itself, but that this change is also subjected to characteristics, typical behavior, bounds and conditions. Regarding the motion of a pendulum, we know that the position changes due to forces that themselves depend on the position. However, since the two dimensions of position and change of position are strongly correlated, not all trajectories are physically possible. A trajectory resembling a circular orbit in this two-dimensional space indicates that the underlying motion is some form of oscillation, as is the case for the pendulum.

However, in order to understand the intricacies of a complex motion it is important to capture the higher order rates of change as well, such as the acceleration, the *jerk* (rate of change of the acceleration), the *snap* (rate of change of the jerk) and successively higher orders. As was the case for the simple pendulum, these orders are not simply independent from one another, but mutually dependent. It is the trajectory of the motion in this space of ever

[2] For instance, 'jerk' of body movement is considered in some contexts to be indicative of exercise-induced fatigue [14], and other jerk-based smoothness metrics for the accomplishment of complex tasks have been also investigated by Gulde et al. [7]

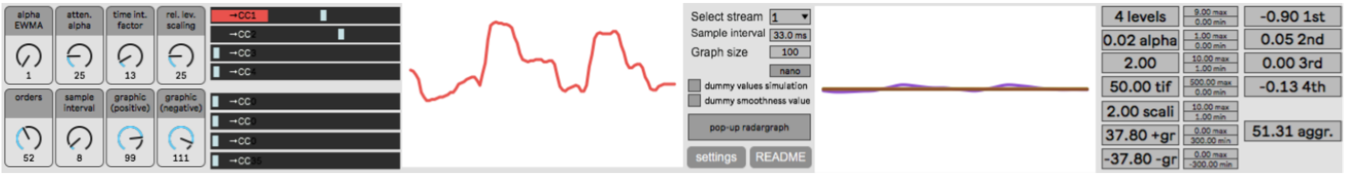

Figure 2: Still image from the SmoothOperator Max for Live device running inside Ableton Live. The macro controls 1-6 on the left of the device correspond to the parameters described in 2.2.

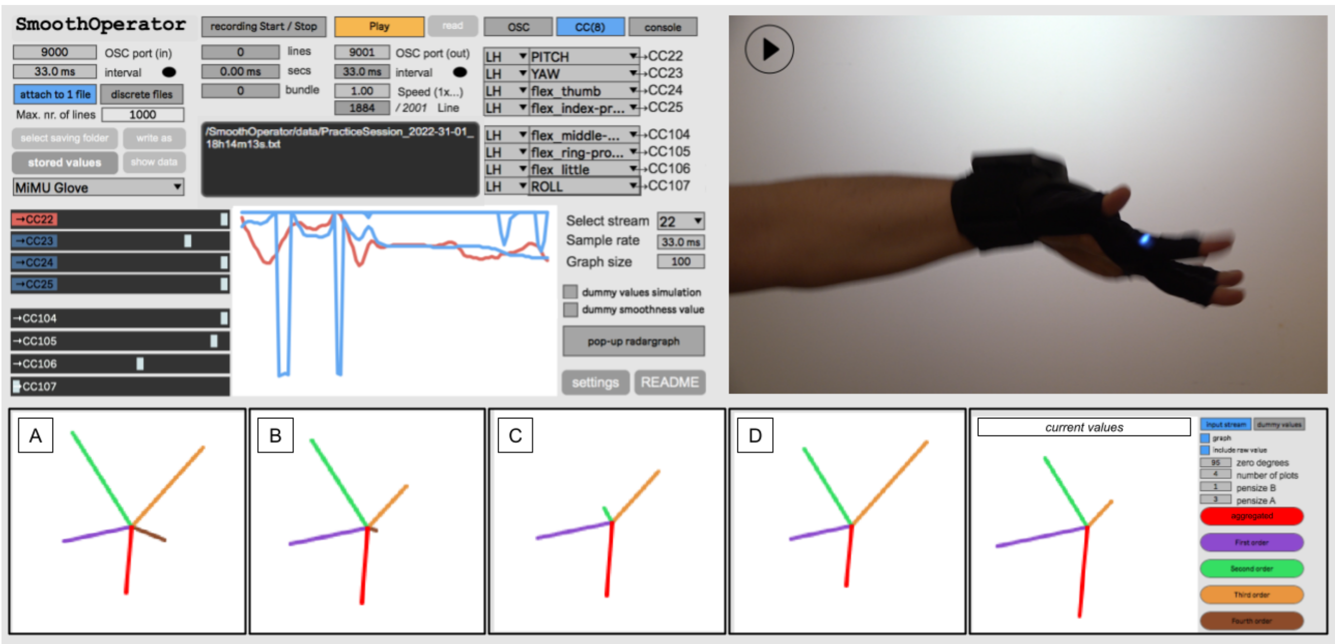

Figure 3: Still image from the user interface of the standalone version of the SmoothOperator: The upper left panel shows recording options and parameter settings. The upper right panel takes in video input for documentation purposes. The radar plots in the lower panel show four user-defined smoothness profiles (labeled A-D) characterized by the *first* (purple), *second* (green), *third* (orange) and *fourth* (brown) orders The vertical line (red) represents the aggregated value.

higher order derivatives that yields the characteristics and eventually a profile of the motion. We suggest this may also be the case in contemporary dance practice, where transitions of gestures might have a characteristic trajectory signature in this abstracted space.

The velocity is mathematically defined as a limit of the difference in position over an infinitesimally close succession of times. In general, any rate of change of a quantity Q is defined in this limiting manner. The velocity is the rate of change of position, the acceleration is the rate of change of velocity and so forth. Formally, the rate of change of Q is defined as:

$$\frac{d}{dt}Q = \lim_{\Delta \to 0} \frac{Q(t) - Q(t-\Delta)}{\Delta} \tag{2}$$

Both our perception and digital recording devices have a finite temporal resolution.[3] This 'graininess' of time is often represented by the Planck-constant and is far beyond the resolution that we refer to when talking about perception and recording.[4] Nevertheless, we henceforth consider only the discrete non-infinitesimal version of the rate of change and its higher orders,

$$\frac{\Delta Q}{\Delta t} = \frac{Q(t) - Q(t - \Delta t)}{\Delta t}$$
$$\frac{\Delta^n Q}{\Delta t^n} = \sum_{k=0}^{n} Q(t - k\Delta t)(-1)^k \binom{n}{k} \tag{3}$$

where the latter follows by induction from the former. Here n is the order of the discrete derivative and k is a summation index. The quantities that we are concerned with in this paper are primarily the raw signals from the capture device, such as the translational motion or the rotation along one of the axes. However Q may also be an aggregated signal, such as the radius.

[3] According to most conventional modern physical theories even nature itself has a certain graininess with respect to its temporal resolution. [3][4]

[4] From the perspective of human perception, that 'graininess' of time has probably more to do with biological perception thresholds, such as the flicker fusion threshold [8]. This and other considerations about perception are, however, beyond the scope of this paper.

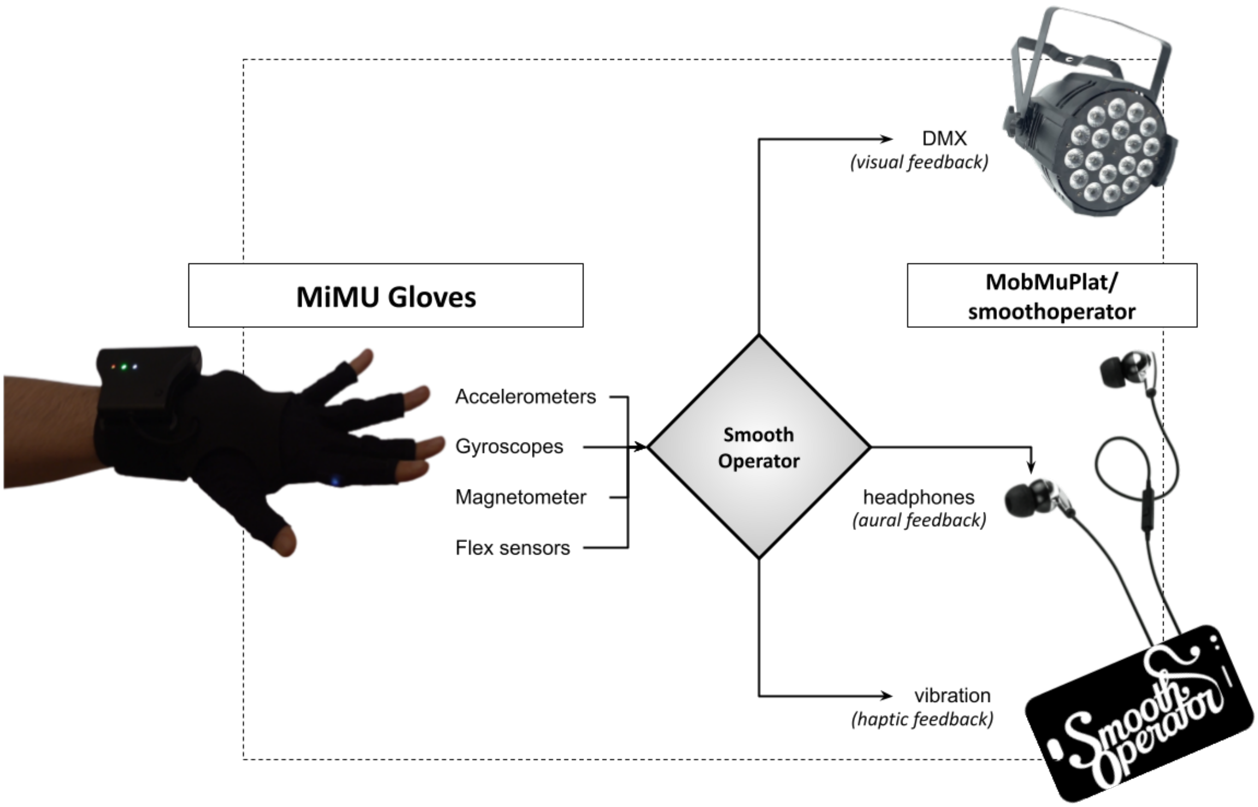

Figure 4: Processing workflow of the inputs and outputs of the SmoothOperator during our case study with the MiMU Gloves.

We calculate the aggregated orders of smoothness from the quantity Q by the following parameterized formula:

$$\begin{aligned} S^k(t) &= \alpha_k \frac{\Delta^k Q}{\Delta t^k}(t) + (1-\alpha_k) S^k(t-1) \\ S(t) &:= \sum_{k=0}^{k=L} \gamma^k \left| S^k(t) \right| \end{aligned} \tag{4}$$

The first equation may be recognized as the definition of an exponentially weighted moving average (EWMA) for the discrete derivatives $\frac{\Delta^k Q}{\Delta t^k}$ at the respective orders k. This EWMA attenuates the signal and makes it more usable for the purposes of artistic movement studies. The attenuation factor α_k is a measure for the effective window length over which the average is taken. A conventional quantity used to measure this effective duration is $\Delta t/\alpha$. We observed that a constant α independent of the order k makes the higher orders more rugged. Hence, we parameterized the attenuation via $\alpha_k = \alpha \cdot f^k$, where $f \geq 1$ is the factor by which the attenuation of successive orders is enhanced. For $f = 1$ all orders are attenuated at the same rate α. All values S^k are initialized to zero, i.e. $S^k(0) = 0$. The second equation sums the absolute values of all contributions up to level L, weighted respectively by a factor γ^k. For $\gamma = 1$ all orders have the same weight, but in practice one may put more emphasis on higher orders.. We also note that we retrieve the discrete version of the C^k-norm for $\alpha = \gamma = 1$. In the following part we discuss out parameter choices.

Alpha Scaling Factor f. We have observed that a higher attenuation factor for higher derivatives yields a better signal-to-noise ratio. We account for this observation by introducing a scaling factor f that decreases the attenuation $\alpha_k = \alpha f^k$. Therefore we constrain $f \geq 1$. In practice we have chosen it to be $f \approx 1.25$.

Attenuation α. We are interested from a performance standpoint in the persistent and non-volatile expression of the various orders of change. The factor α is inversely related to the window size for the EWMA. In practice we have chosen small values of $0 < \alpha \leq 1$ around 0.01 or smaller.

Time Interval Factor. This parameter gives the user the option of scaling the time interval, set by the *sampling rate*.

Level Scaling Factor γ. From the practitioner's perspective the higher order derivatives are the most counter-intuitive and insightful. For that reason we have introduced the level scaling factor γ. We also require $\gamma \geq 1$. In practice we found values of $\gamma \approx 1.25$ to be the most insightful.

Orders L. The number of orders of differentiation. We have typically set $L = 4$.

Figure 5: Dancer Maria Shurkhal practicing with the SmoothOperator. On the Left, Maria explores the device using only the sonification feature. On the right, some moments from the recording of a practice session involving sonification and interactive lighting (in this session, the smartphone is attached to the dancer's belt).

Sampling Rate Δt. For our purposes we chose $\Delta t = 0.33$ seconds.

3 DEVICE

We implemented a tool that calculates the aggregated orders of smoothness from a constant stream of data as described in 2.2, and yields a graphic representation of the 'smoothness space' as shown in Fig. 3.

In addition to the plotted graphs displayed on the UI,[5] we experimented with different kinds of visual, aural and haptic feedback in the context of dance practice sessions. Visual feedback was achieved by modifying hue and brightness of the stage lights, sending color information to a DMX lighting system.[6] Users could define up to four different 'profiles' (i.e. positions in *smoothness space*) arbitrarily associated with the lighting colors red, violet, blue and green. The ensuing stage lighting was the result of the interpolation of RGBW values between the predetermined positions. The aural feedback is a beeping signal whose change in *speed*, *pitch*, envelope *shape* and *waveform* is proportional to the first, second, third and fourth smoothness orders of the motion. We finally experimented with the smartphones' vibration feature to provide haptic feedback to the dancers: based on a previously defined narrow region of the smoothness space, performers wearing the smartphone attached to their bodies (Fig. 5) would receive a buzzing cue when movement characteristics match the predefined ones.

4 CASE STUDY

We tested the prototype of the Smooth Operator using the MiMU Gloves,[7] which provide a good combination of Magneto-Inertial Measurement Units as well as flex sensors in a compact wearable device. We processed individual streams of movement data (e.g. pitch, yaw, and roll dimensions of the dancers' hand movements) which were then aggregated to yield an overall smoothness profile. We found particularly useful to define in advance a specific region in 'smoothness space' which performers set up to explore, a practice-based method we came to call *targeted movement exploration*. In

[5] The standalone version (c.f. Figure 3) of the SmoothOperator can fetch sensor data directly via OSC from any OSC-capable device. Additionally, there is a *Max for Live* device version of the SmoothOperator which can be hosted in Ableton Live (c.f. Figure 2), and takes Continuous Control (CC) midi messages as input.

[6] Specifically, we send DMX messages with color information according to the RGBW protocol.

[7] https://mimugloves.com/

tests involving full body motion we used built-in smartphone sensors[8] to gather motion data (i.e. motion along the x, y and z axes) and send it to the *SmoothOperator* via OSC. Led primarily by the sonification, dancers began to identify and loosely differentiate between 'qualities of smoothness', and quickly went on to suggest more sophisticated combinations of movements to probe.

5 CONCLUSIONS AND FUTURE WORK

We see our work as a preliminary exploration of the smoothness space, and further research is necessary to verify any claim about the validity of the smooth descriptor. Although this paper is only concerned with movement in 3D space, the quality of smoothness is of course not exclusive to movement. In principle, the SmoothOperator can take in and process any kind of data stream, which opens the door to all sorts of cross-media artistic experimentation.

ACKNOWLEDGMENTS

We would like to thank MiMU Gloves. This research was realized within the scope of the artistic research project *Atlas of Smooth Spaces in the audiocorporeal Arts* financed by the FWF Austrian Science Fund (AR 640).

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[8]We used the *MobMuPlat* application to run a *Pure Data* patch on a smartphone device. That patch would send sensor data from the smartphone to the SmoothOperator, and receive smoothness data from SmoothOperatorin real time via OSC messages.