

Multimedia Music with Dance

Dance the Music

Gwangyu Lee

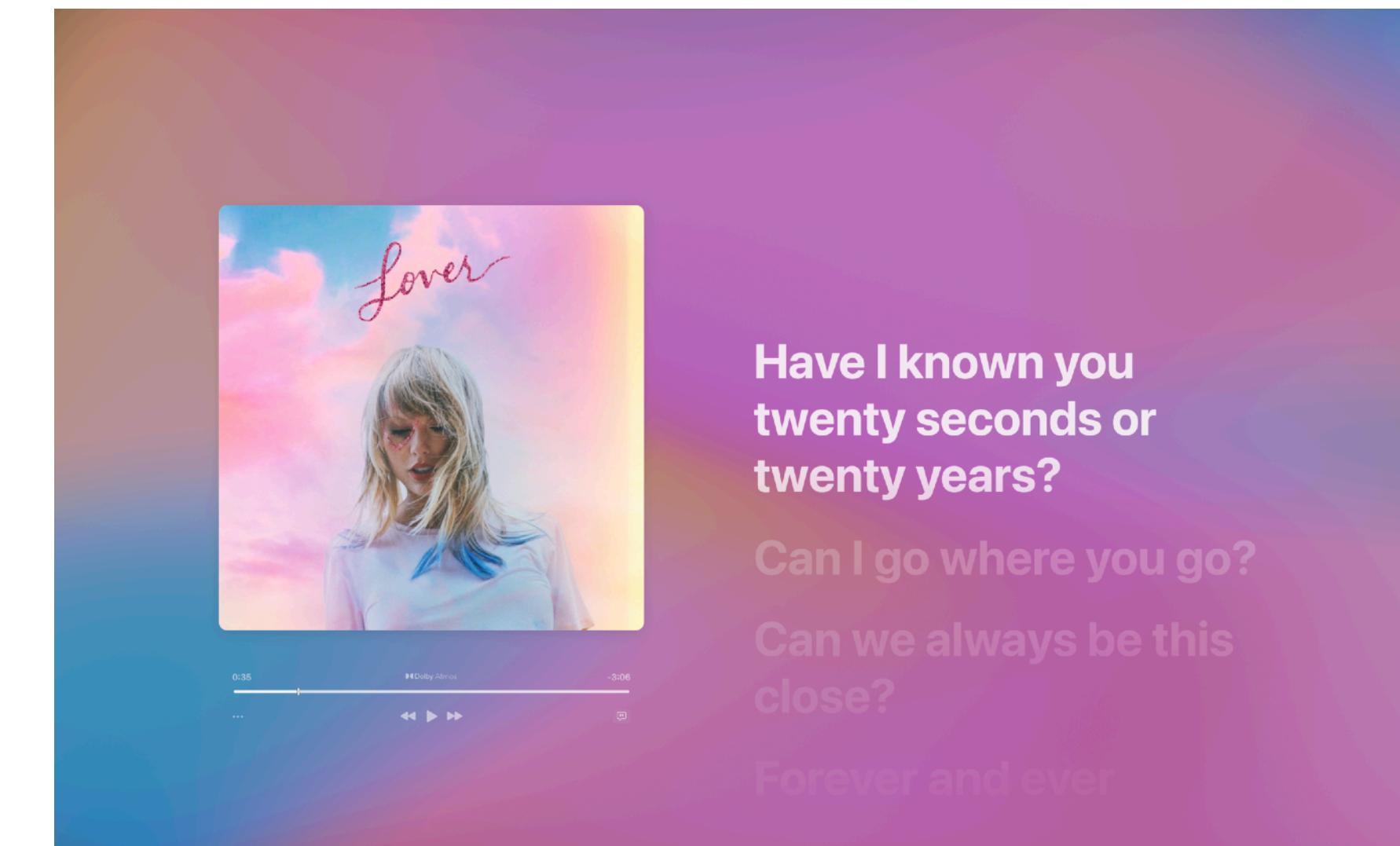
Gypsy Jazz



Tango







**What if the dancers could “Dance the music”
rather than “Dance to the music”?**

Interactive Dance

Tchaikovsky



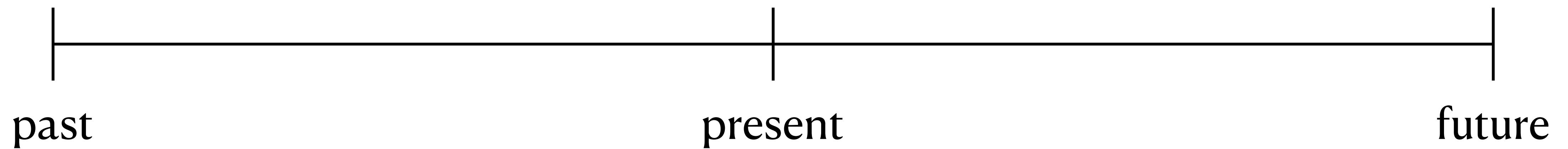




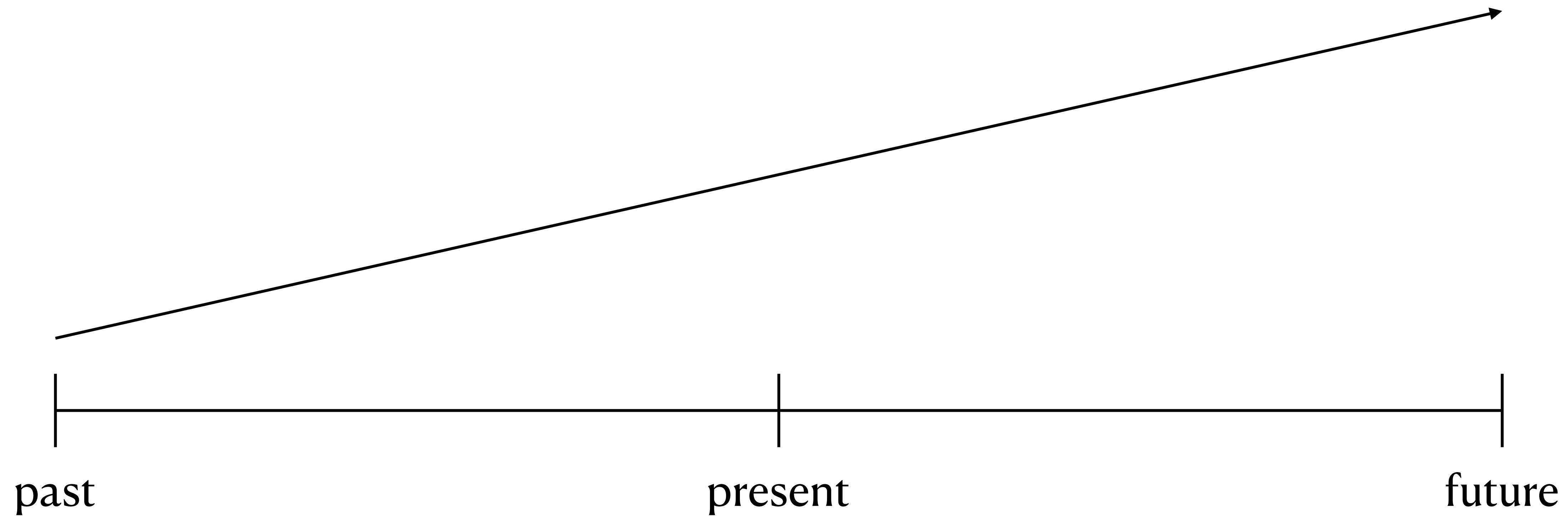
**“Audio content and visual content
in multimedia cannot be broken down
into two independent elements”**

Why Interactive Dance?

Linear-time

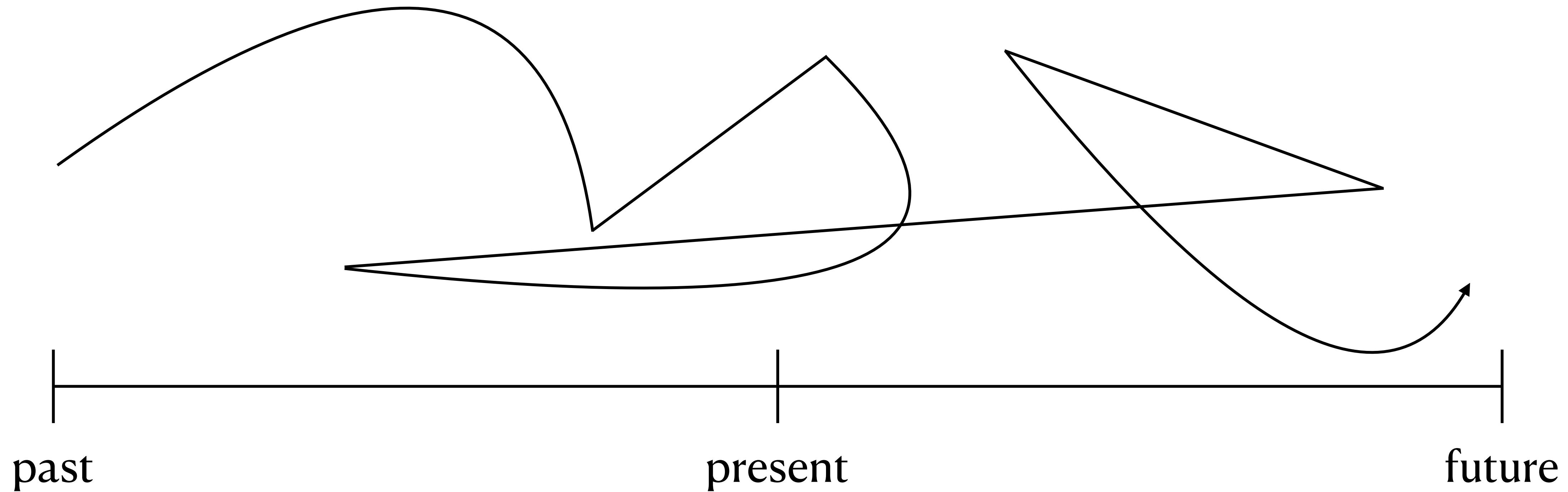


Linear-time



Real-time

Real-time



Motion-Tracking Technologies

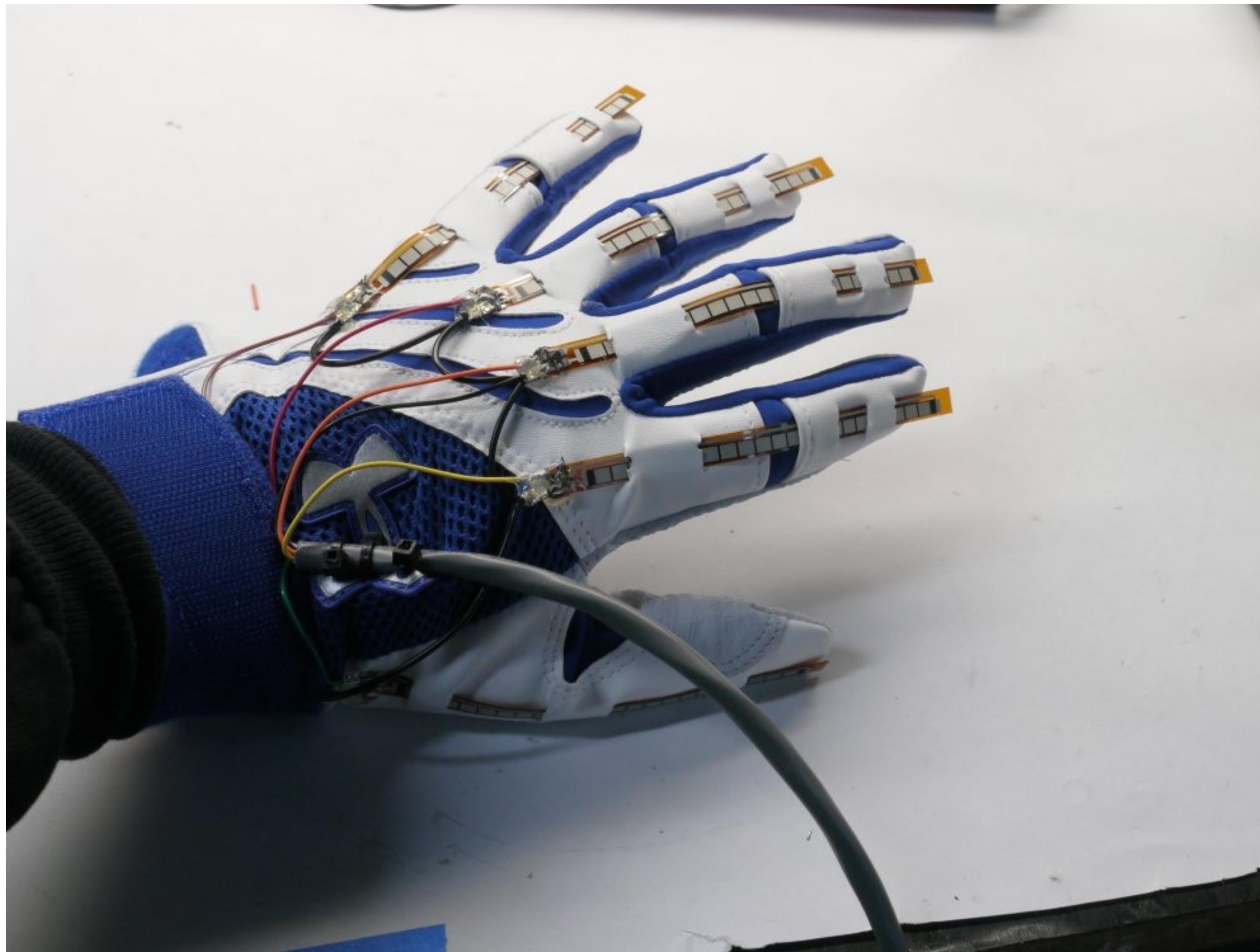
Motion-Tracking Technologies

- Inside-In
- Inside-Out
- Outside-In
- Camera-based motion-tracking systems(Computer Vision)

Inside-In



Inside-In



Inside-Out





<https://youtu.be/S-T8kcSRLLo?feature=shared&t=419>

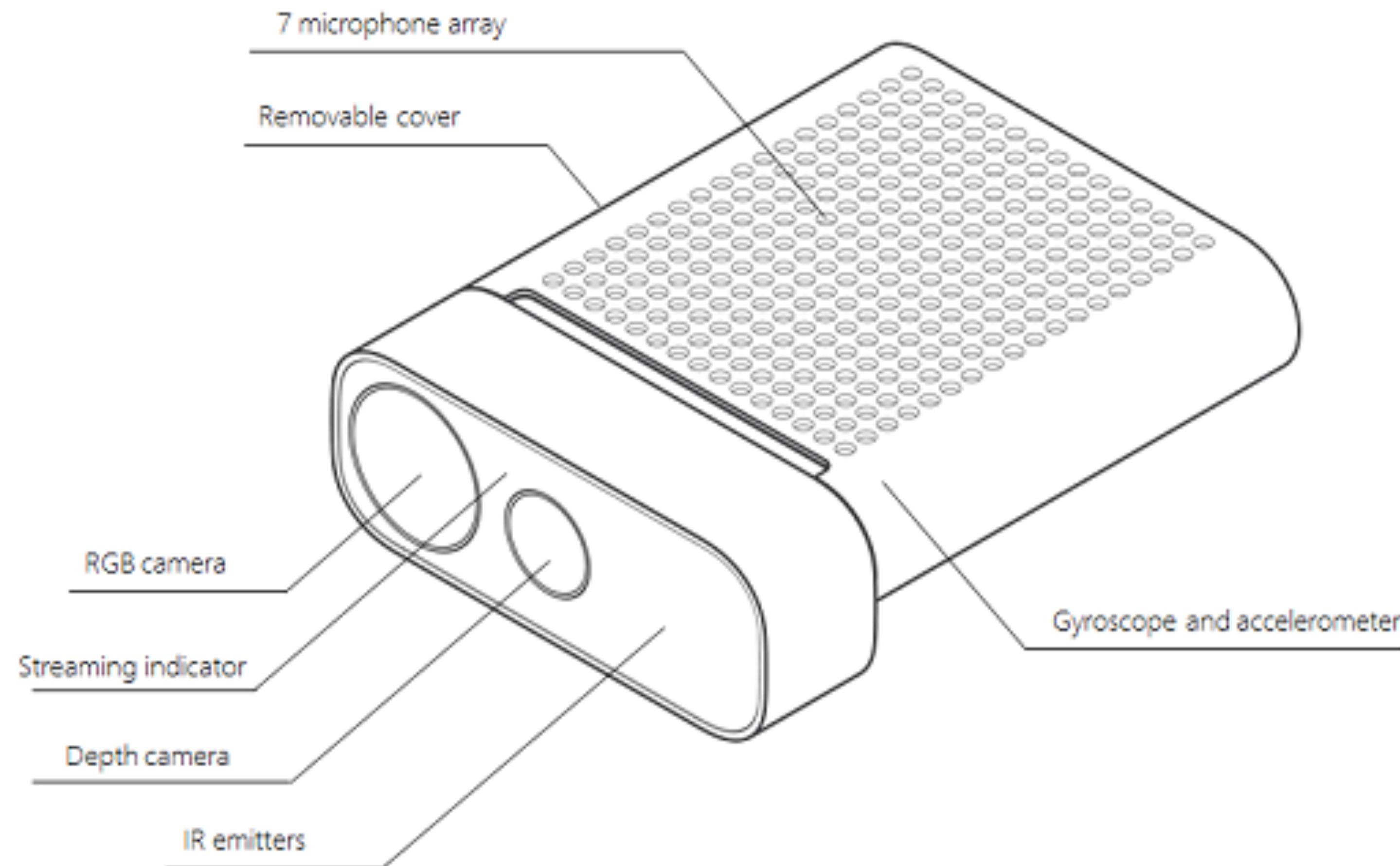
Outside-In



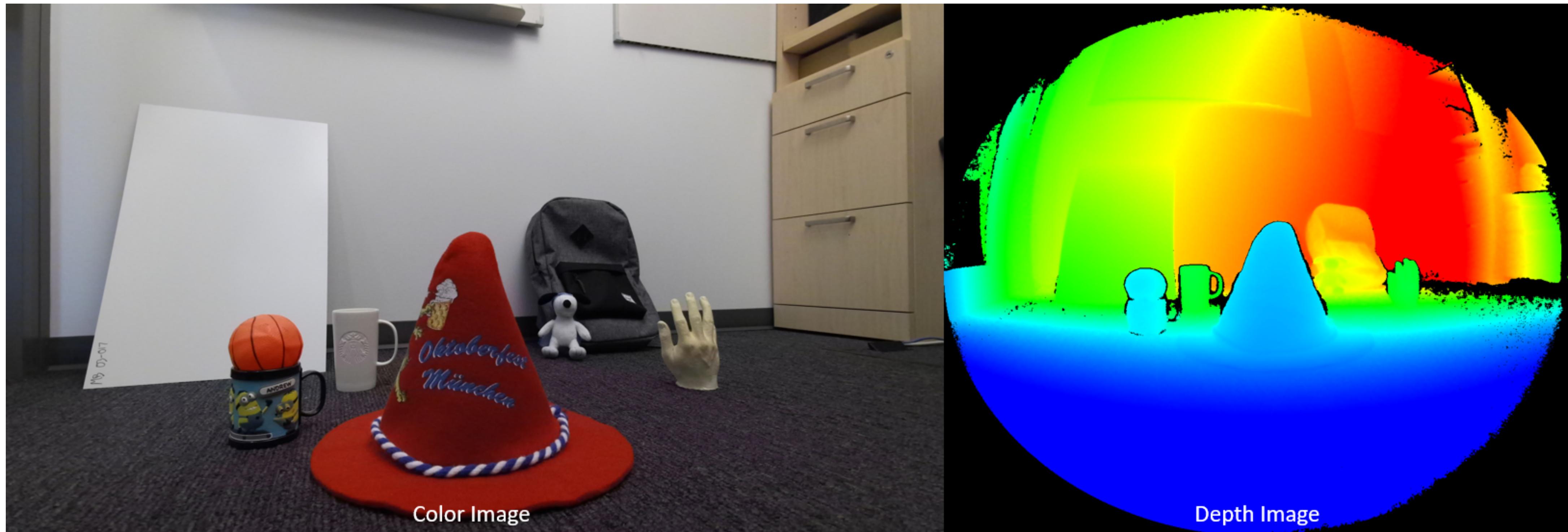
Outside-In



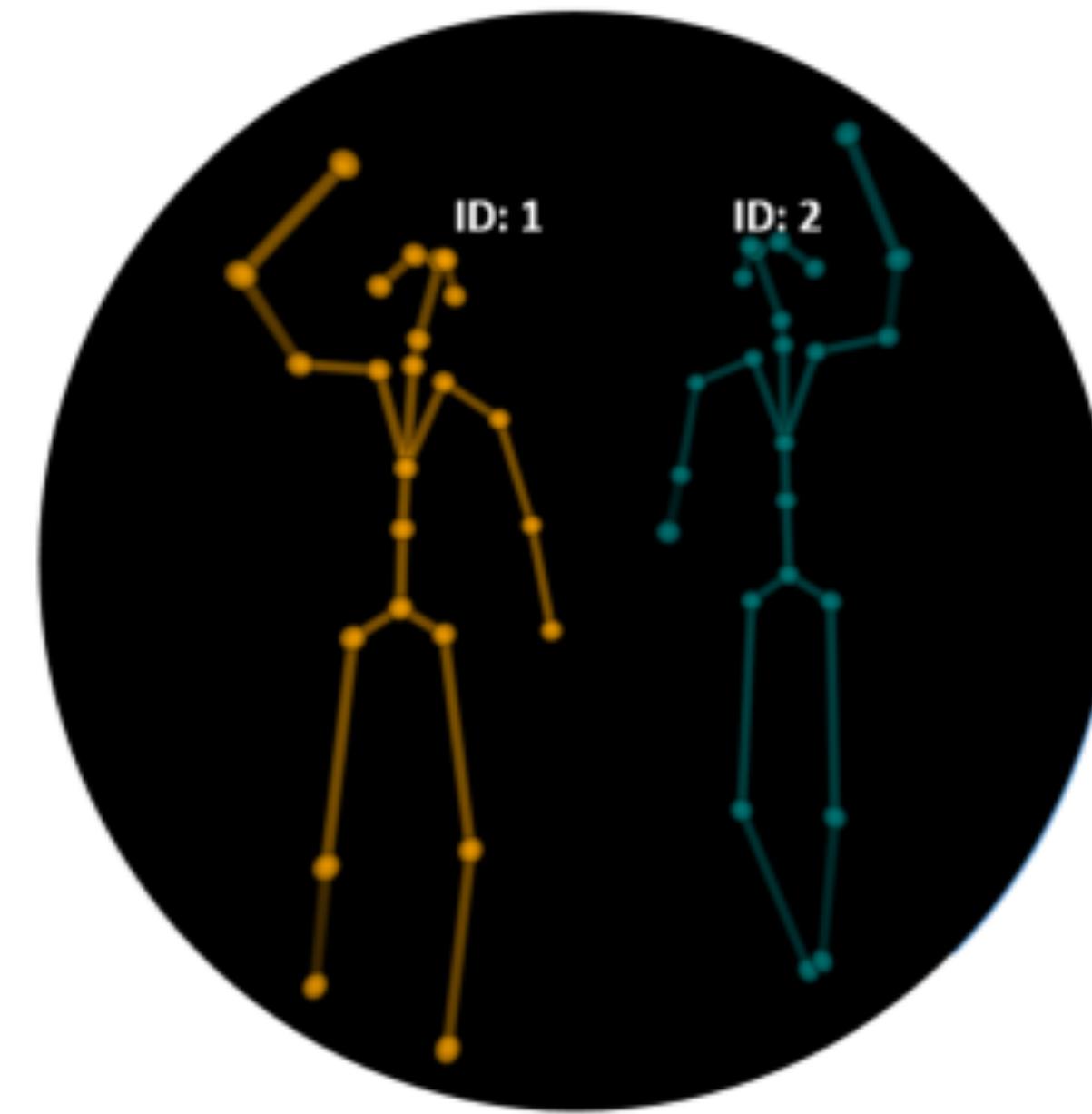
Azure Kinect DK



Azure Kinect DK



Azure Kinect DK



Kinect for Windows 2 (29/29 fps)

[WIKI] [FORUM] [TUTORIALS] [D] 60 FPS: 18 Realtime 7:30:19 1 Operators deleted.

Pane Layout New Layout + / project1

Transform transform1

Transform Post

Group

Transform Order Scale Rotate Translate

Rotate Order Rx Ry Rz

Translate 0 0 0

Rotate 0 0 0

Scale 1 1 1

Pivot 0 0 0

Uniform Scale 1

Normals Maintain Length On

Look At

Up Vector 0 1 0

Forward Direction -Z

Sep 25, 2017 — The face Right below the "calibrate" V1.X Documentation - V1 Documentation: User interface Skeleton tracking - Documentation 4.4 OSC (Open Sound Control) More results from forum.n community.troikatronix.co Motion Capture/Tr Oct 28, 2017 — Motion C Mate and I have managed outgoing port number in N community.troikatronix.co [ANSWERED] Kin it ... In terms of a comparison spatial trigger point calibr

oscin1 null1

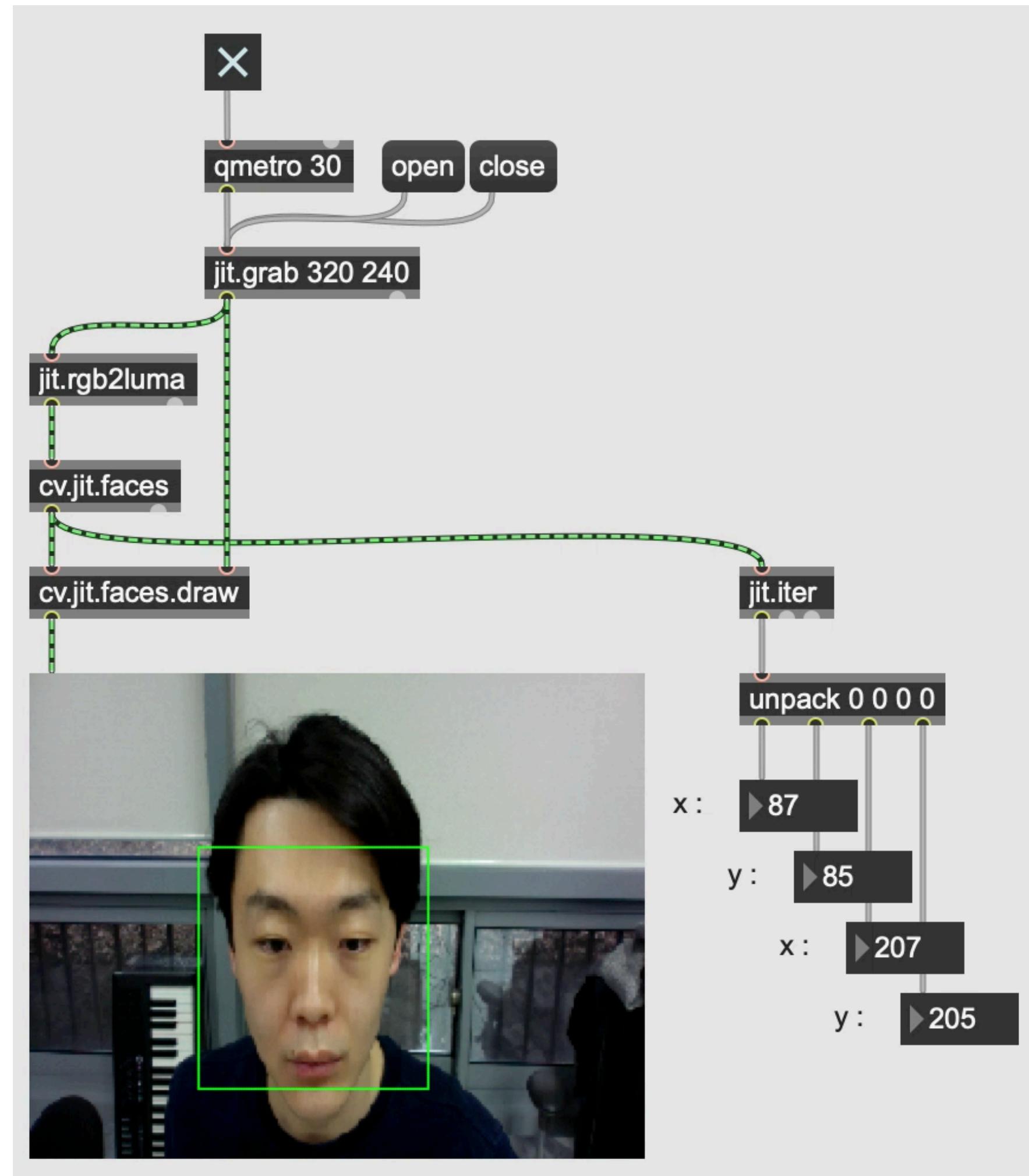
sphere1 transform1

Start: 1 End: 600
RStart: 1 REnd: 600
FPS: 60.0 Tempo: 120.0
ResetF: 1 T Sig: 4 4

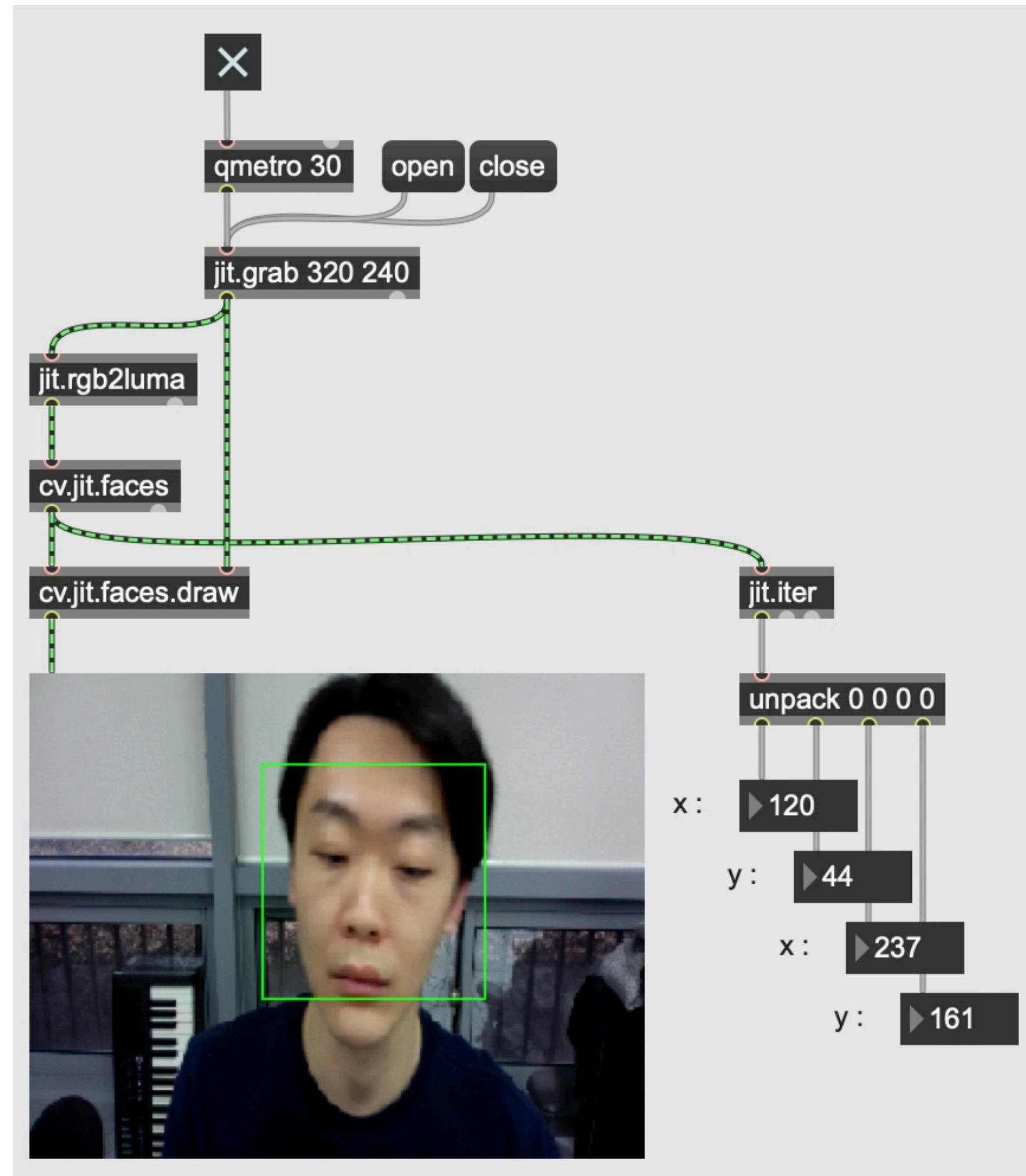
TimeCode 1 Beats 00:00:08.55 536 Range Limit Loop Once

/ Time Path: /

Computer Vision



Computer Vision



Link

Computer Vision

cv.jit.shift: track an image area

cv.jit computer vision for jitter

The cv.jit.shift object implements two closely-related algorithms for tracking a window in a greyscale image: MeanShift and CAMShift.

In MeanShift, a starting window is defined and the image centroid (see cv.jit.centroids) is computed inside this window. The window is then shifted so that it is centered on this centroid. This process is repeated until the window doesn't move.

CAMShift (Continually Adapting MeanShift) works similarly but the size and orientation is adjusted at each iteration.

In both cases, the result is that the window will tend to center on bright spots. This can be used to track blobs and works on greyscale and binary data.

Source: Movie File
File: Tennis-ba...
or drop file here
Rate: ▶ 1.
Enable resize
320 ▶ 240 Size
Enable binary
50 Threshold
Enable rgb2luma
Invert

tol ▶ 0.1 vexpr \$f1 / 255.
fade ▶ 0.2 prepend color 0.
jit.chromakey @mode 1 @minkey 1.
@maxkey 0. @tol 0.1 @fade 0.2
jit.rgb2luma
cv.jit.shift
mode ▶ 0
distance ▶ 2.
maxiters ▶ 10
cv.jit.shift.draw
p make_rect Use the "rect" attribute to set the search window's starting position.

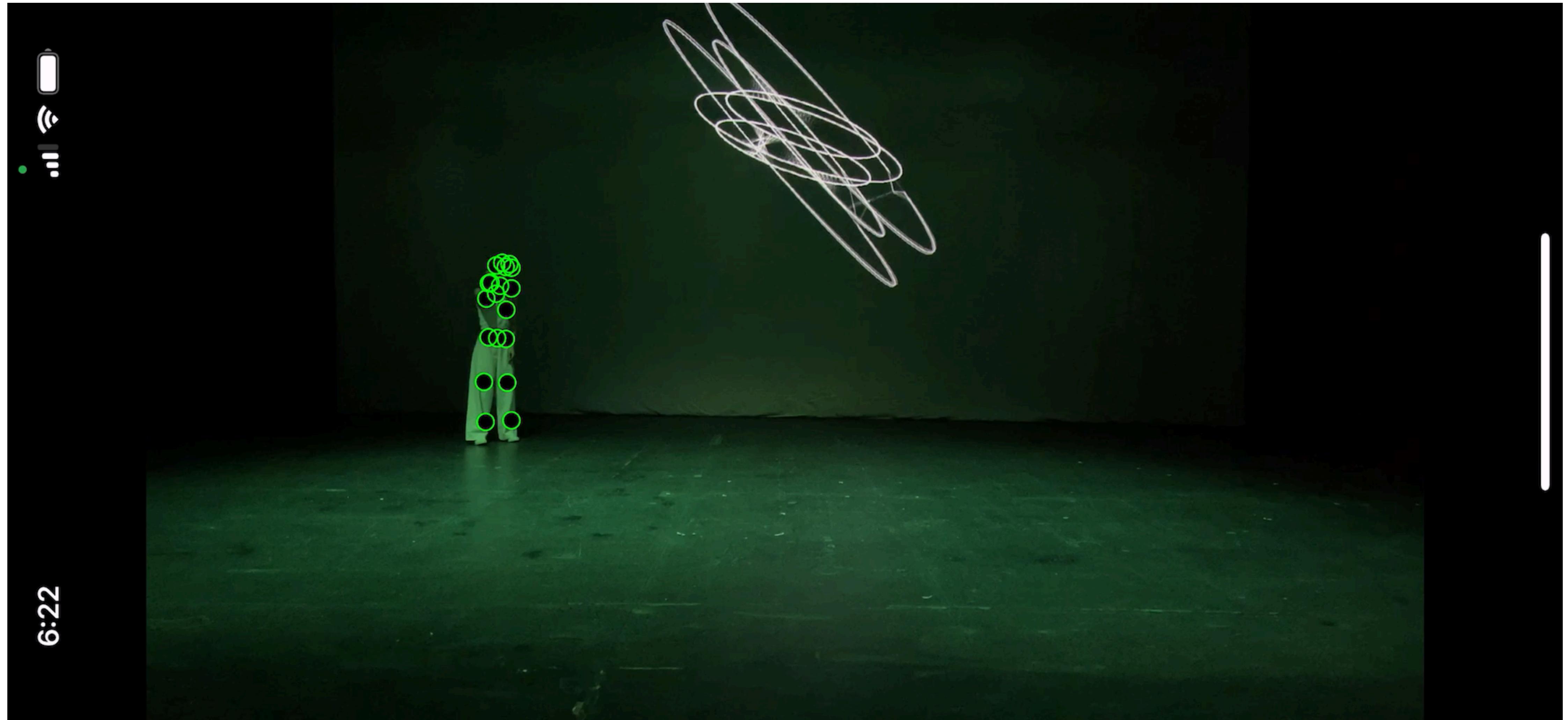
Input: Single-plane char
Output: 4-element list: New window coordinates
8-element list: Vertices of rotated window
float: Mass of window

First, click on this pwindow to select a colour to track...
...then click and drag on this pwindow to set the search window's starting position.

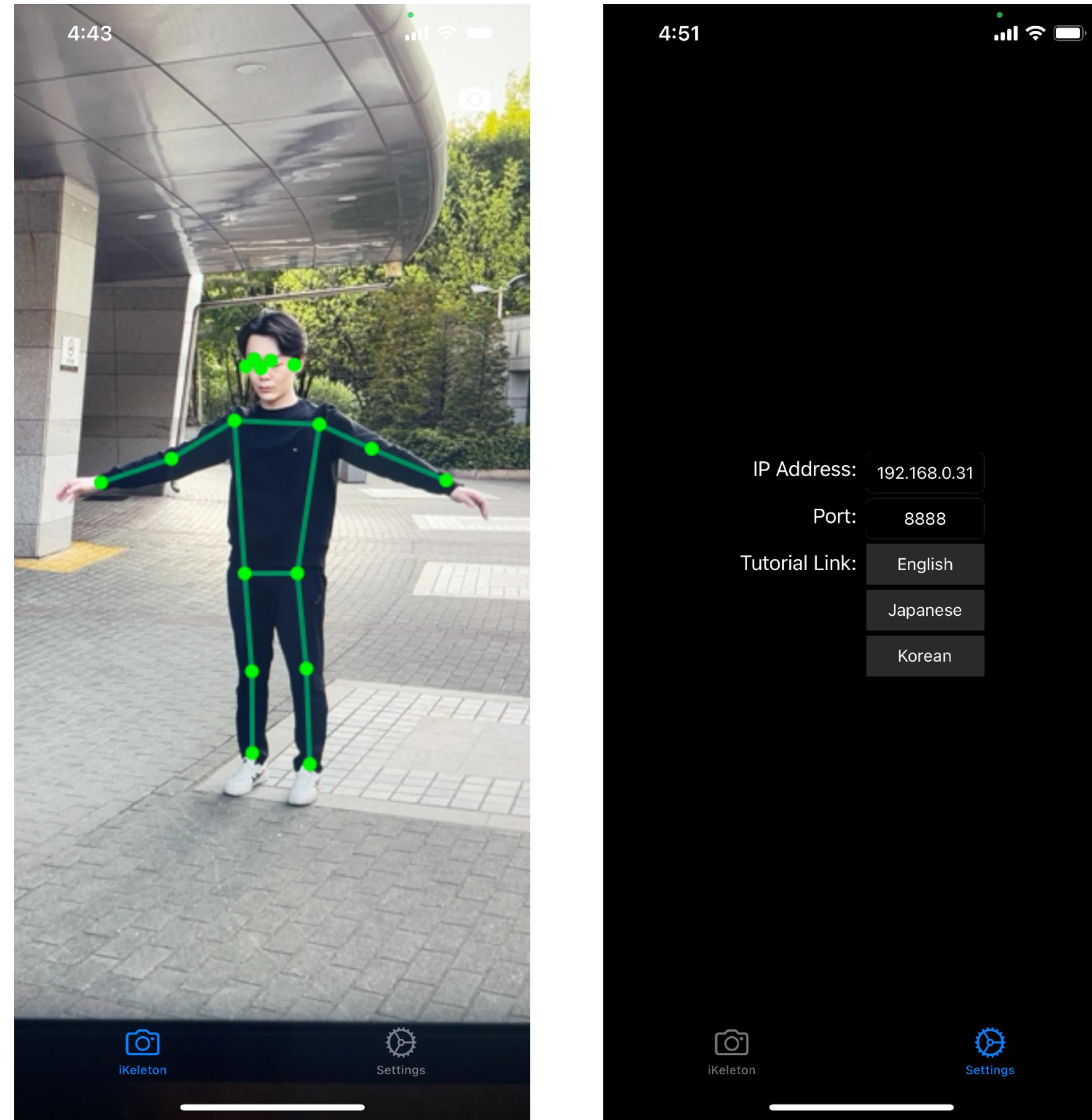
By Jean-Marc Pelletier
jmp@jmpelletier.com
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Link

Computer Vision & Machine Learning



Computer Vision & Machine Learning



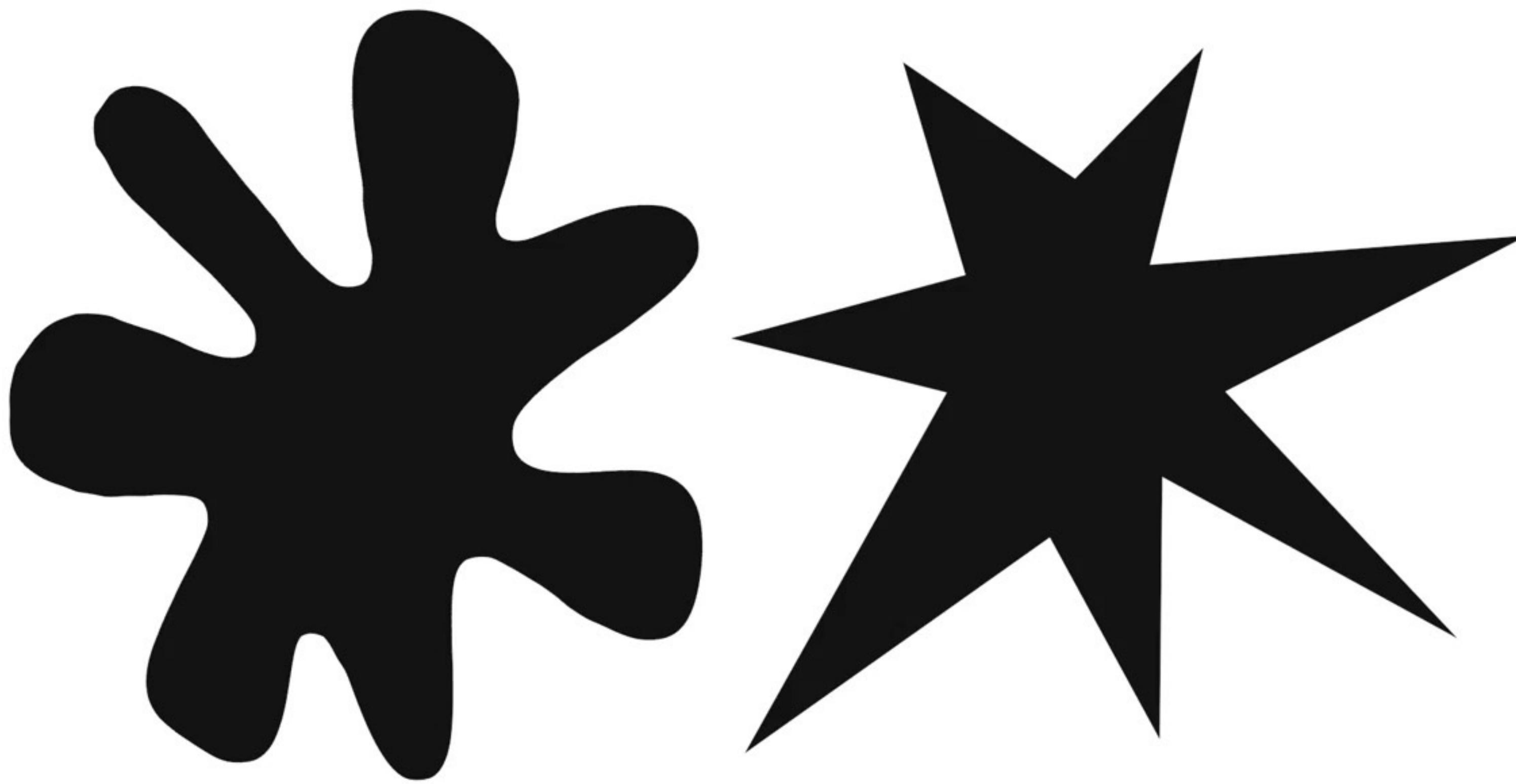
Link

Mapping Motion To Music

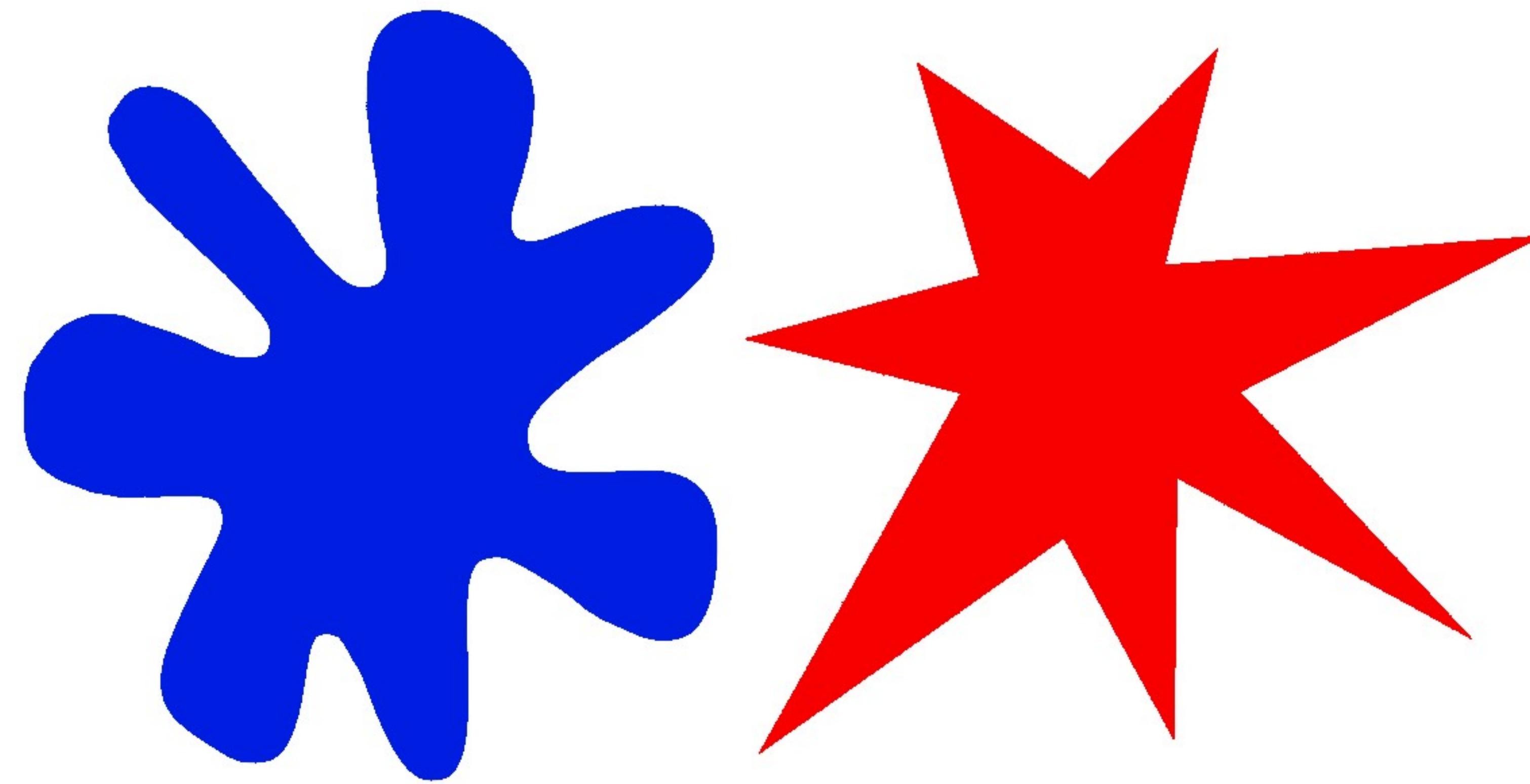
Kick Drum vs Fade Out



Kiki & Bouba

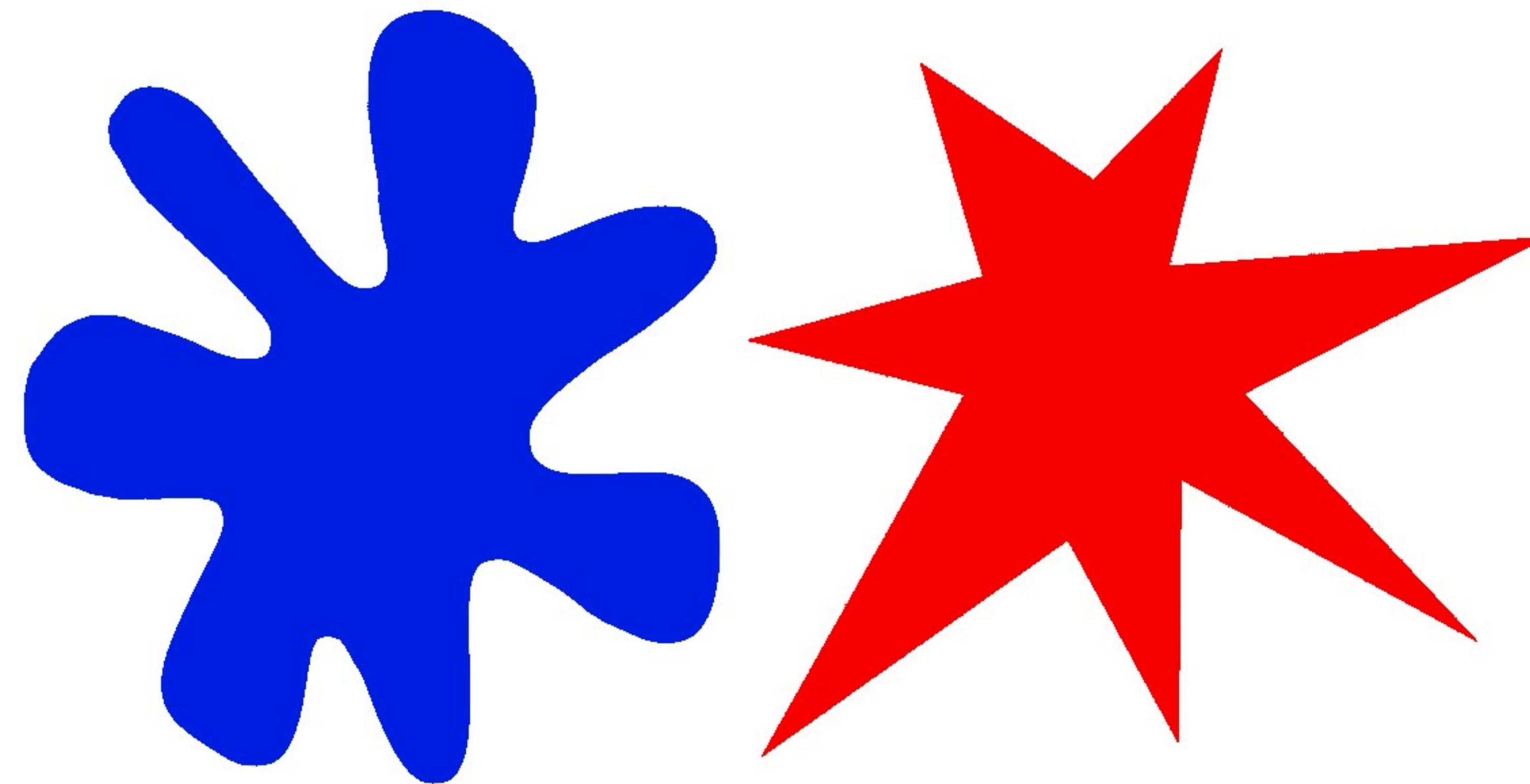


Link

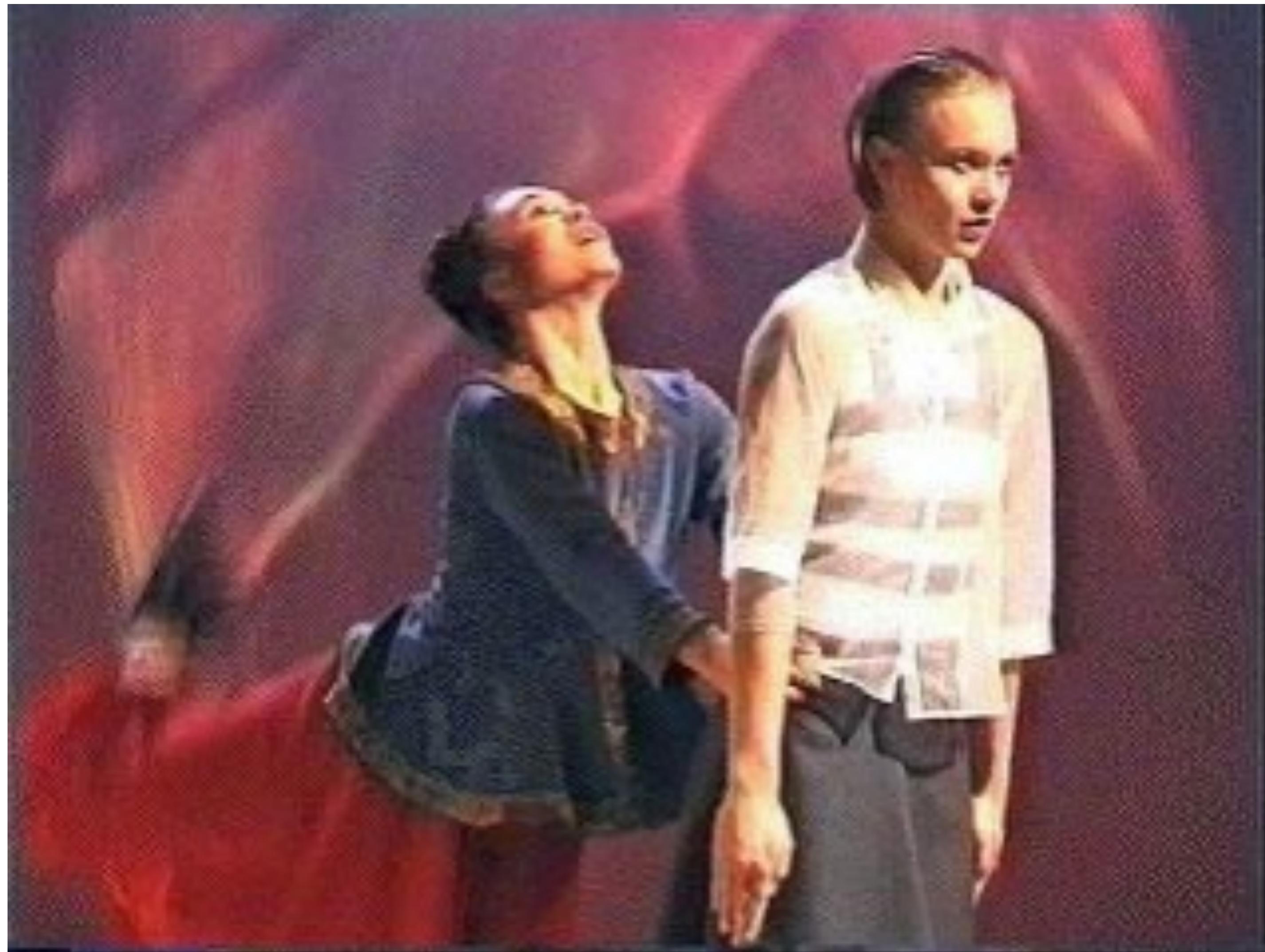


Link

Bouba & Kiki



Sisters



<http://waynesiegel.dk/wp-content/uploads/2013/08/Sisters.pdf>

Pandora Project

Pandora Project

- Workshop
- Experiments
- Sketches

Liquid



Who



The Box



Fire



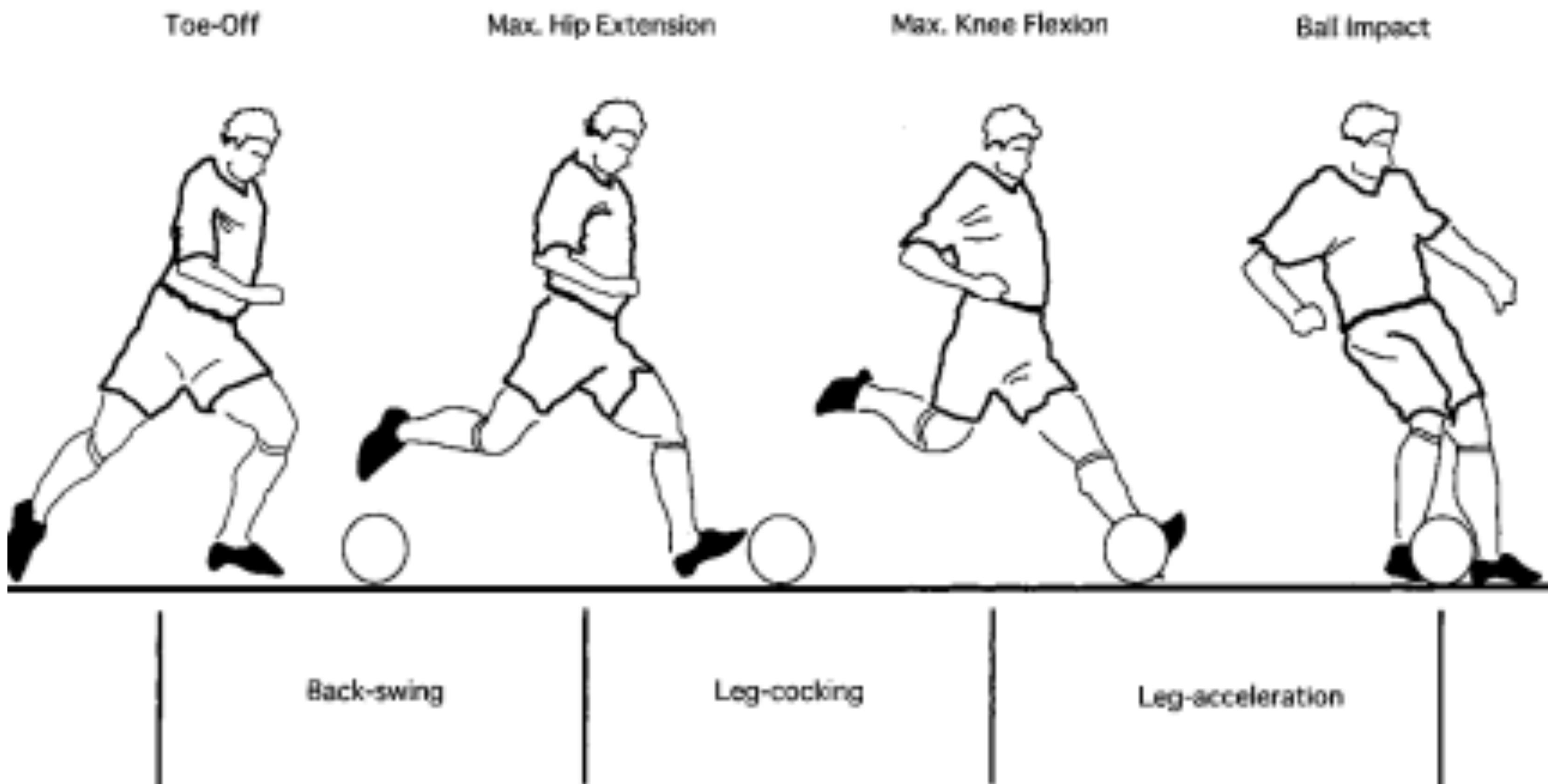
Circles





Gesture Interaction

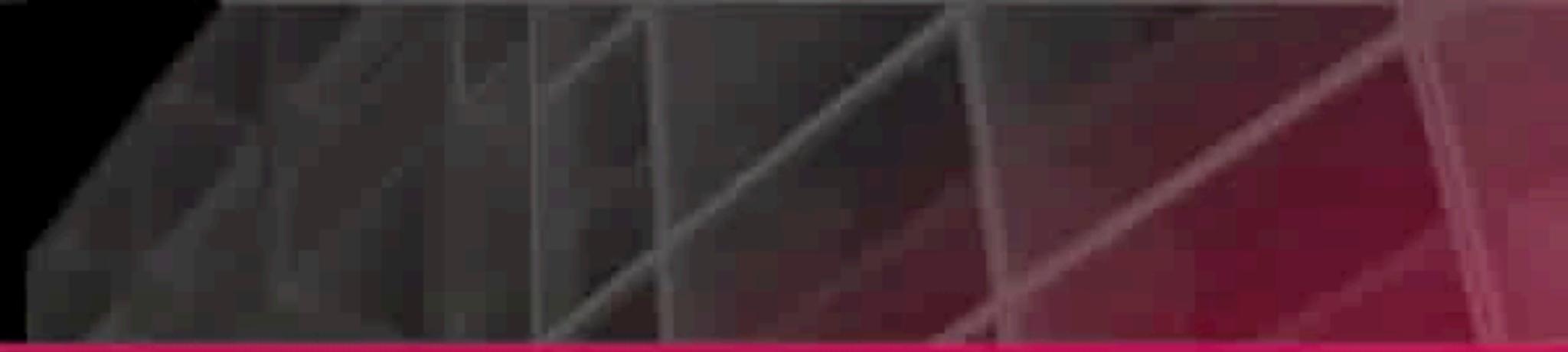
Gesture



Radio Baton



COMPUTER
HISTORY
MUSEUM



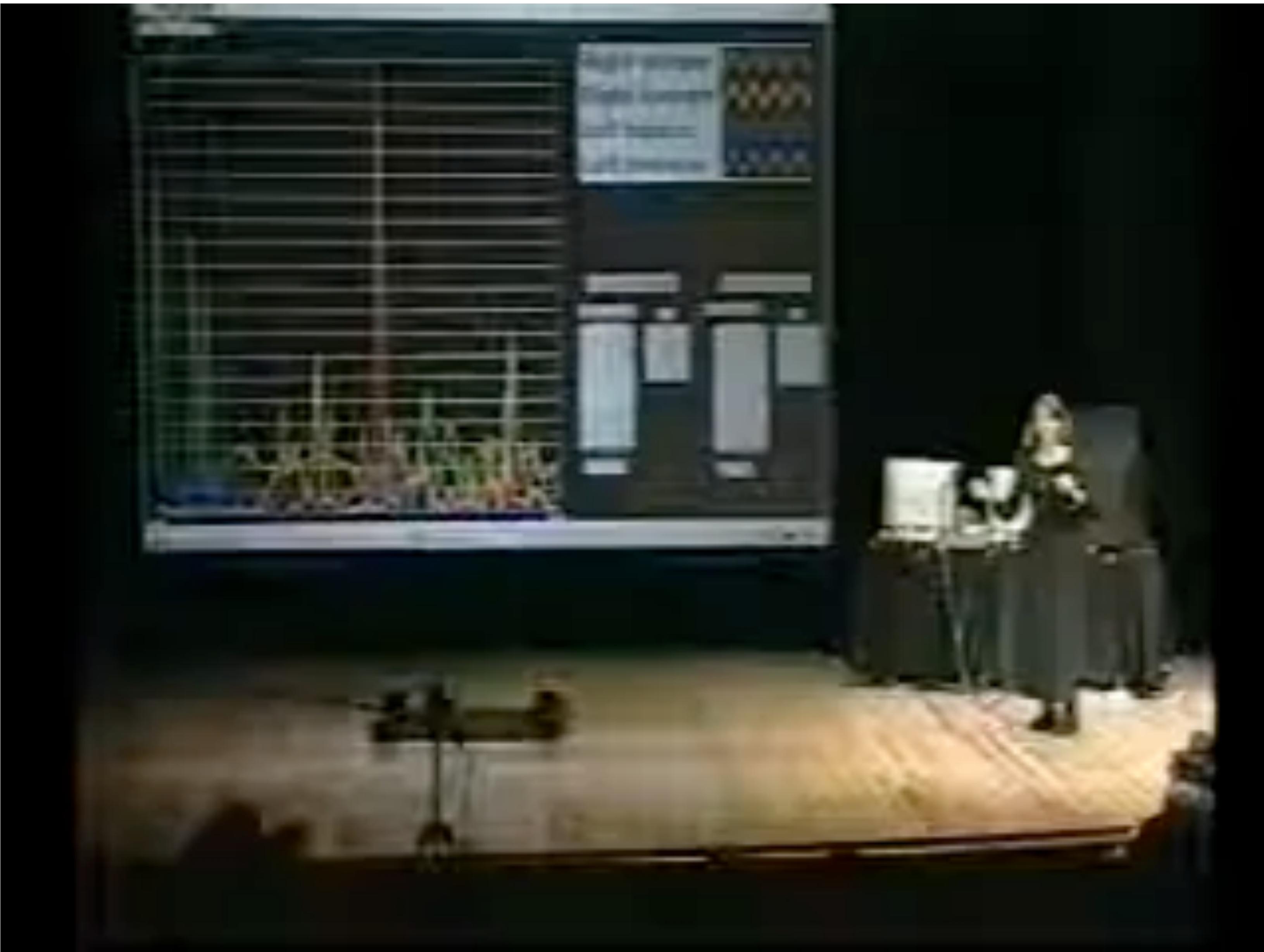
Max Mathews Radio Baton Demonstration

April 7, 2010
Running time 30:48

Where Computer History Lives

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Conductor Jacket



<https://youtu.be/Lnpij7MSRFYM?feature=shared>

UBS Virtual Maestro (aka “Conductor Hero”)

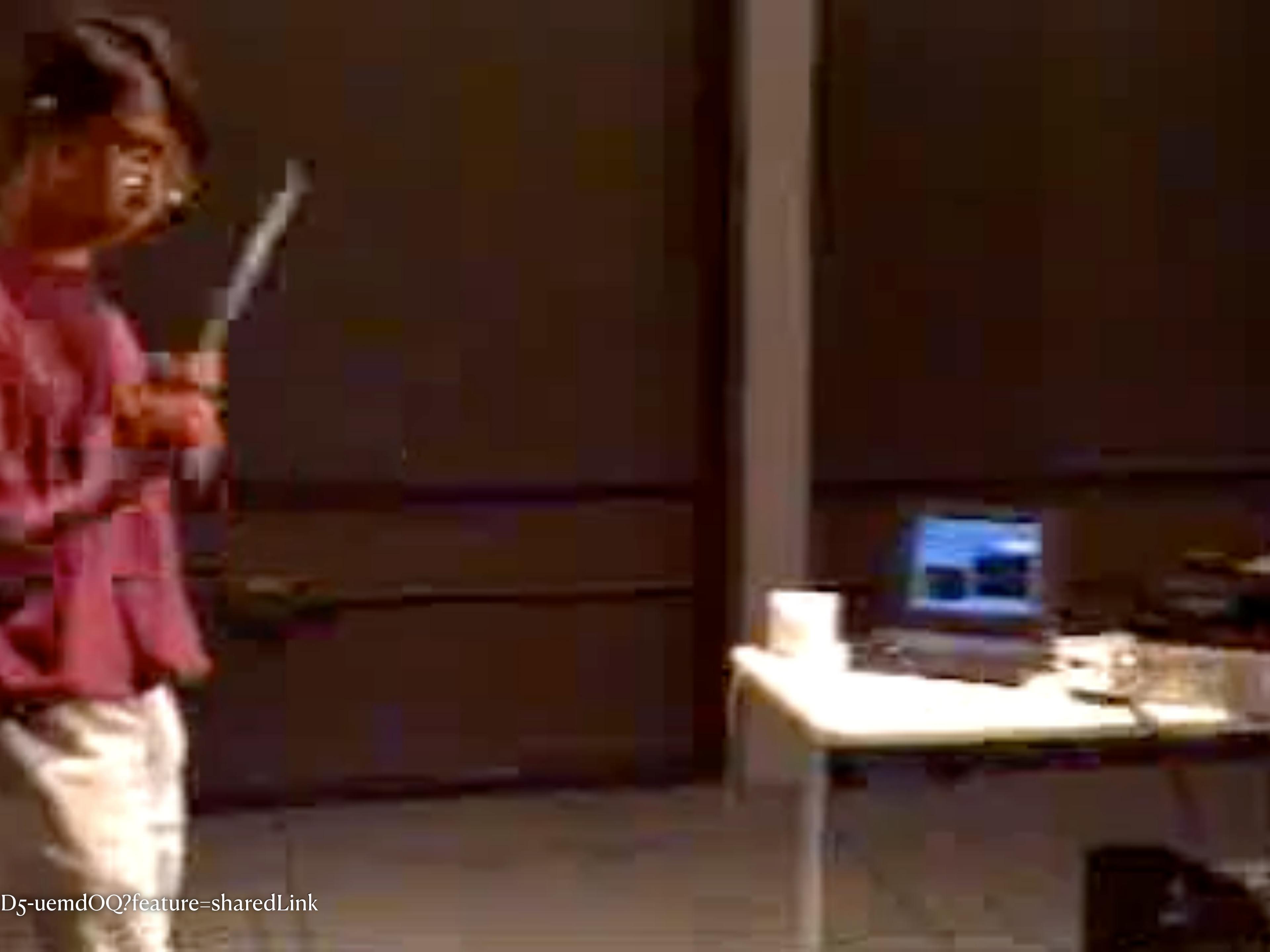


Rationale for Selecting Wii Remote



<https://youtu.be/eJuIS2-wdfU?feature=shared>

Brain Opera: Digital Baton



<https://youtu.be/qAD5-uemdOQ?feature=sharedLink>

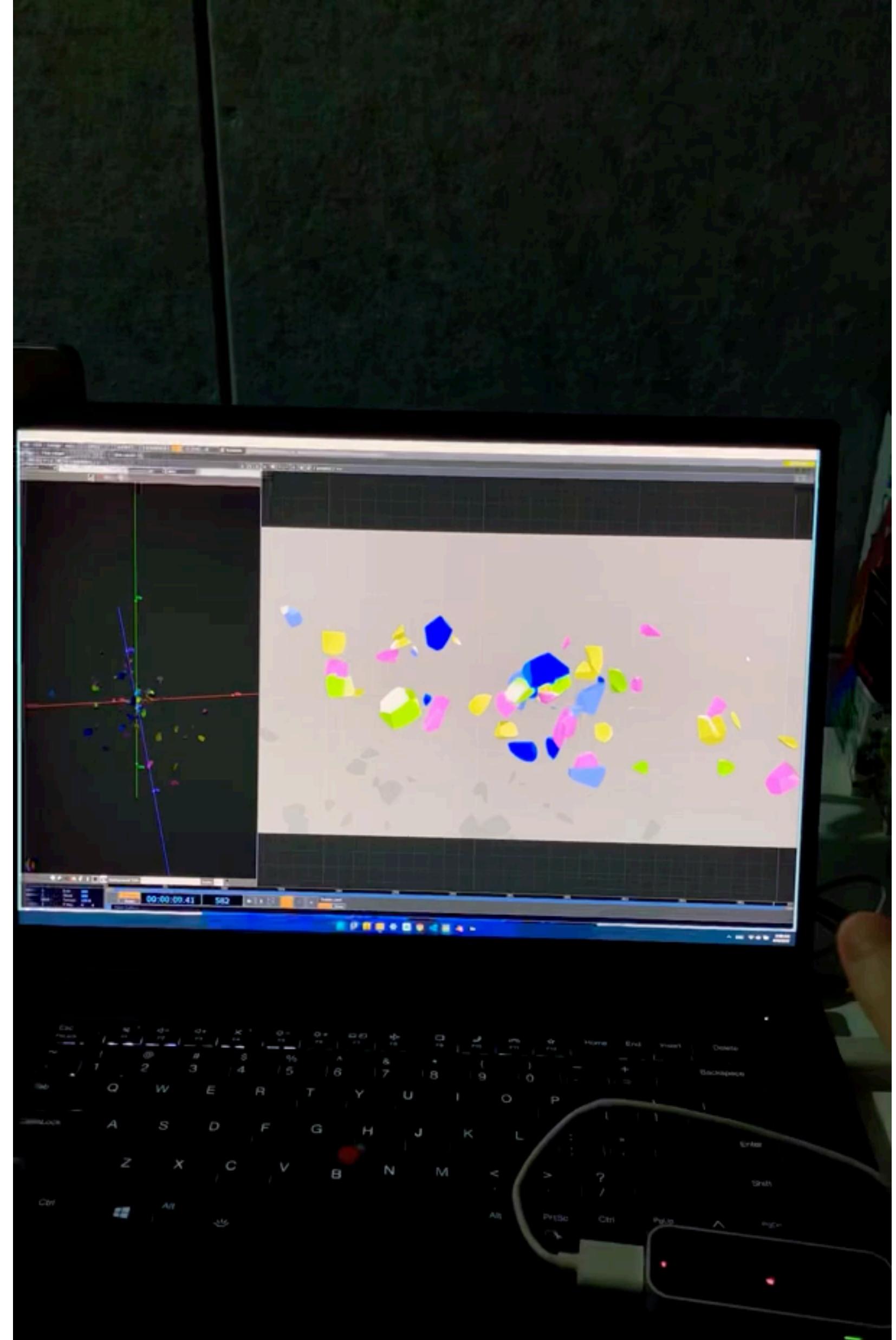
Brain Opera: Sensor Chair

<https://youtu.be/qAD5-uemdOQ?feature=sharedLink>

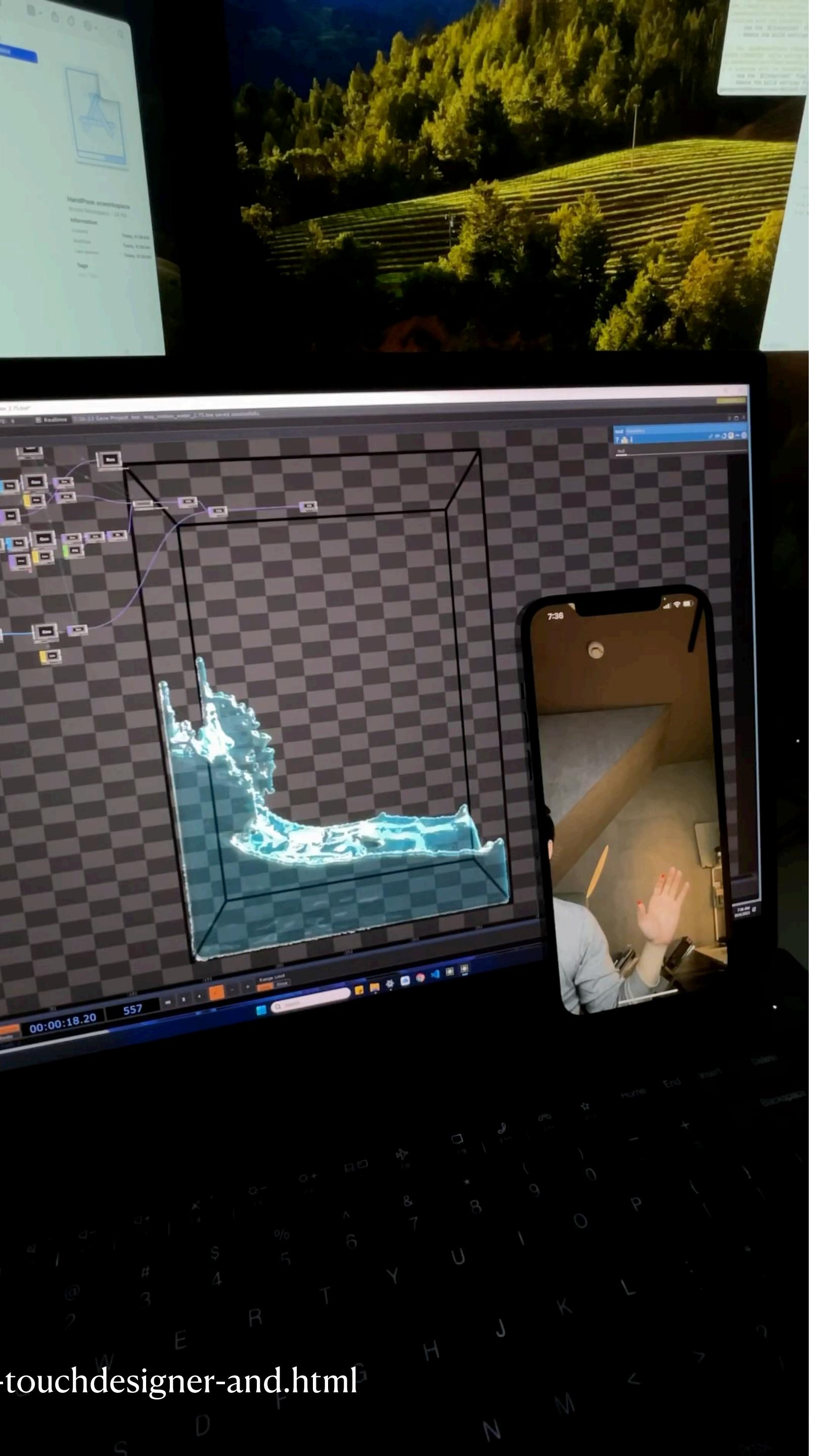
Leap Motion



Link



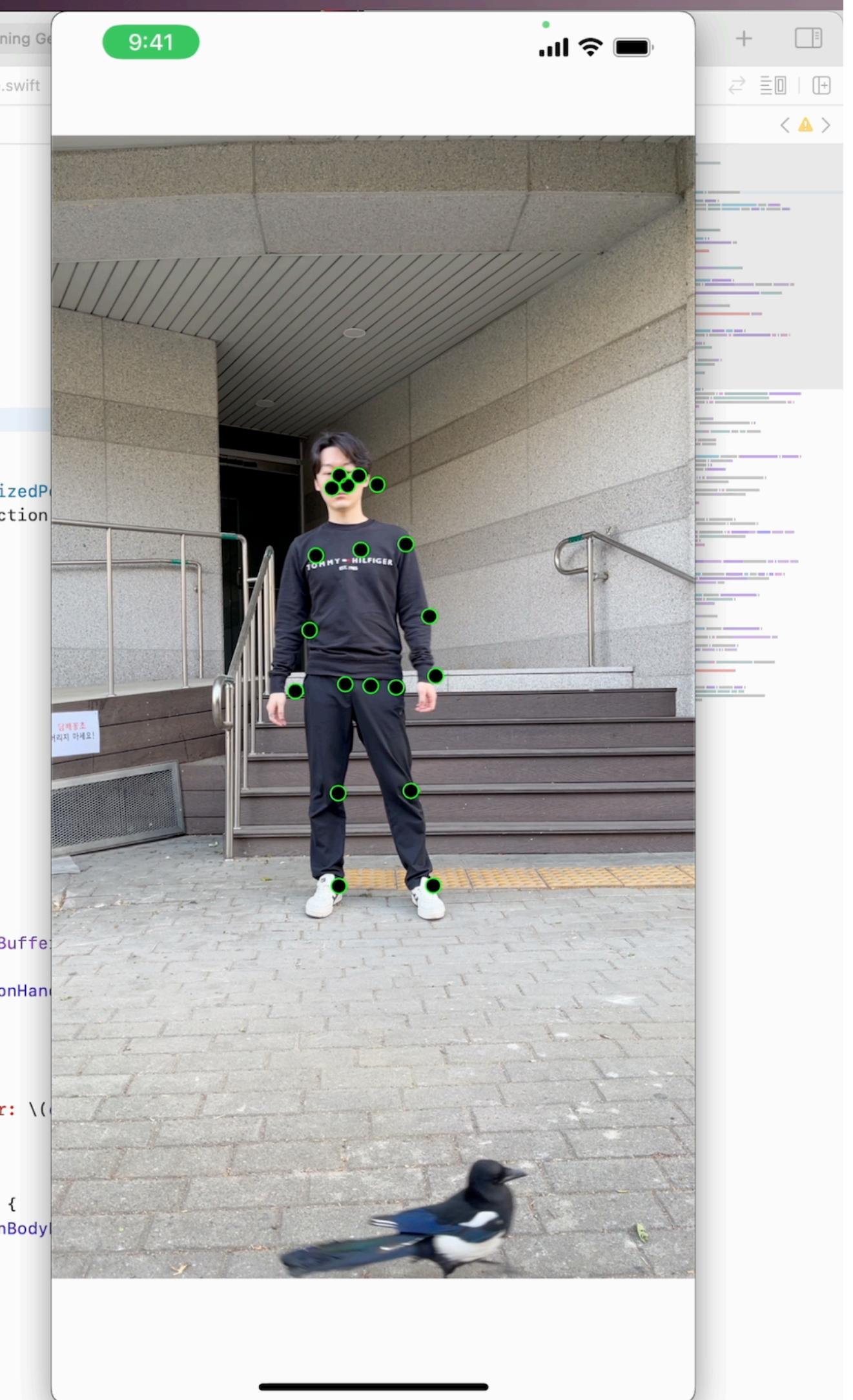
[Link](https://www.gwangyulee.com/2022/04/destroyed-sphere-with-touchdesigner-and.html)





Link

Machine Learning



Line: 12 Col: 55

Left_Side_Up_Down: 0.7800001715777114
Left_Side_Up_Down: 0.7559067606925964
Left_Side_Up_Down: 0.7168729305267334
Left_Side_Up_Down: 0.672476053237915
Left_Side_Up_Down: 0.7200350761413574
Left_Side_Up_Down: 0.7167853713035583
Left_Side_Up_Down: 0.5382627248764038
None: 0.528468132019043
None: 0.7785956859588623

All Output Filter

An interactive system using gesture recognition for multimedia performance

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Abstract

The production of interactive multimedia performances by combining music, visuals, and dance has been attempted using various equipment. This study aims to develop an interactive system using machine learning to classify gestures. To keep the system simple, an iPhone and CoreML were used with an app to classify gestures and send the detected gestures and level of correspondence through a network. The data received were used to control music and visuals on a computer.

Keywords

Gesture recognition; Machine learning; CoreML; Music; Visuals; Dance.

1. Introduction

Music, visuals, and dance are different art forms, although they are inseparable. Most music performances go with visuals and dance; it is difficult to find a music performance that does not include visuals or dance. However, in most performances, dancers follow the music, taking their cues from predetermined directions while visuals are

independent. What if music, visuals, and dance could interact in a single multimedia performance [5]? Such systems have been attempted in the past [1-3, 5-12]. For example, visuals have been changed according to the amplitude of the music or the movement of the dancer, music changed according to the dancer's movement [14, 15], and so on. Consider an interactive multimedia performance of the dancer's movement. If the dancer's hands are raised, the music and visuals change. If the composer wants to use the movement only in a particular part, the operator should turn off the signal of the movement in the rest of the piece. If so, what if the computer could identify the dancer's gesture and use it in the interactive multimedia performance? This study aims to create an interactive system for multimedia performance using gesture recognition. The programs used are Max/MSP¹ and TouchDesigner² on a computer, with machine learning used for gesture recognition.

2. Machine Learning Model Design

This study uses machine learning to identify a specific gesture. Machine learning, a field of artificial intelligence, uses computer algorithms that automatically improve

¹ Max/MSP, also known as Max/MSP/Jitter, is a visual programming language for music and multimedia developed and maintained by the San Francisco-based software company Cycling '74.

² TouchDesigner is a node-based visual programming language for real-time interactive multimedia content, developed by the Toronto-based company Derivative.

through experience. In this study, we chose CoreML, which applies a machine-learning algorithm to a training dataset to create a model, allowing the iOS app to run the models locally.



Figure 1. CoreML workflow³

2.1 Rationale for Selecting CoreML

A machine-learning program using a computer-vision system that receives the motion signal in real time is required to identify the dancer's motion. It can be implemented using an ordinary webcam or Azure Kinect DK [2, 4, 13]. However, there are some reasons that we chose to use CoreML and the iPhone's camera in this study. First, they keep the system simple. If we used an ordinary camera and machine learning, we would need one more program on the computer. In contrast, a camera and machine learning can be integrated into one iPhone.

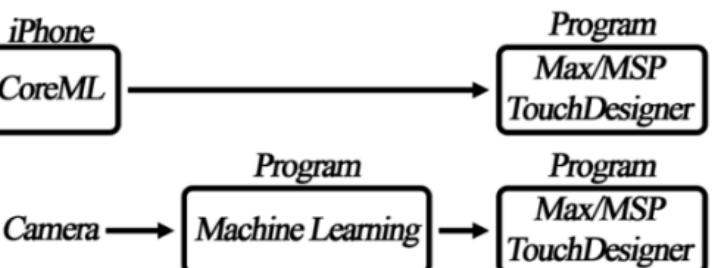


Figure 2. System architecture comparison

Second is the possibilities available with mobile phone cameras. Cell phone cameras are developing tremendously quickly, and a machine-learning model using a LiDAR sensor or more could be applied in future studies.

The last reason is portability. Anyone with an iPhone can implement the system without limits on time or place.

2.2 Rationale for Using Machine Learning

Why use machine learning? Compare previous methods with the data from machine learning.

For example, in the motion of raising a hand, what is the difference between mapping data by obtaining coordinates and recognizing a specific gesture using machine learning? Machine learning can distinguish the direction the hand is moving. Of course, one could write a program to distinguish the direction. However, machine learning is simpler and more effective.

The change in the y-axis is the same when raising the hand to the side and raising it forward. The result is the same even if the speed value of the movement is obtained. However, machine learning allows the capture of various data by separating the components of the hand or other parts of the body's movement.

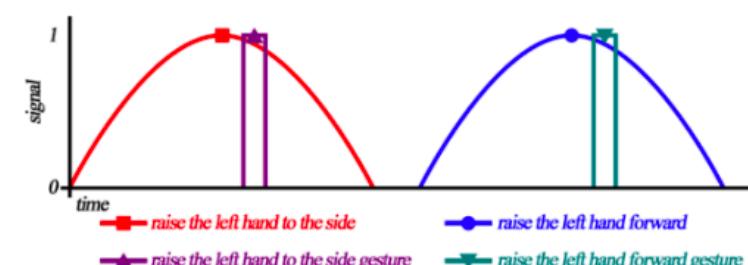


Figure 3. Comparison between y-axis measurement and machine learning

2.3 Dataset for Machine Learning

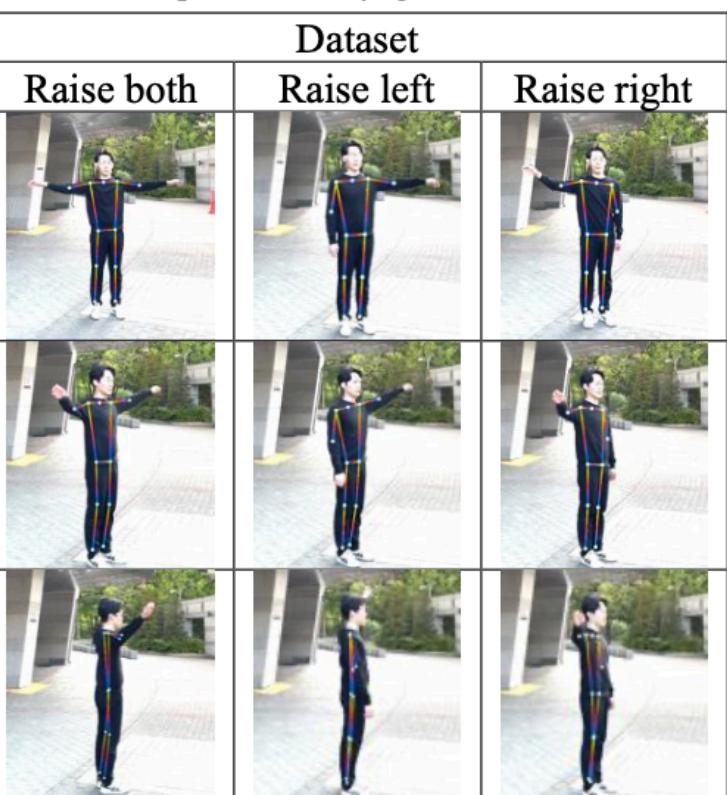
We had to prepare videos for the machine-learning dataset. This study classified six gestures (raising both hands to the side, raising the left hand to the side, raising the right hand to the side, raising the left hand

³ <https://developer.apple.com/documentation/coreml>

forward, raising the right hand forward, and no movement).

Table 1 shows examples of sideways gestures. Videos taken from various angles were edited at two-second intervals. The gesture of raising the hand forward was organized similarly. There were 40 or more videos per gesture.

Table 1. Examples of sideways gestures from the dataset



2.4 Results of Machine Learning

We built three machine-learning models, each of which went through 300 iterations. The results and graphs are as follows.

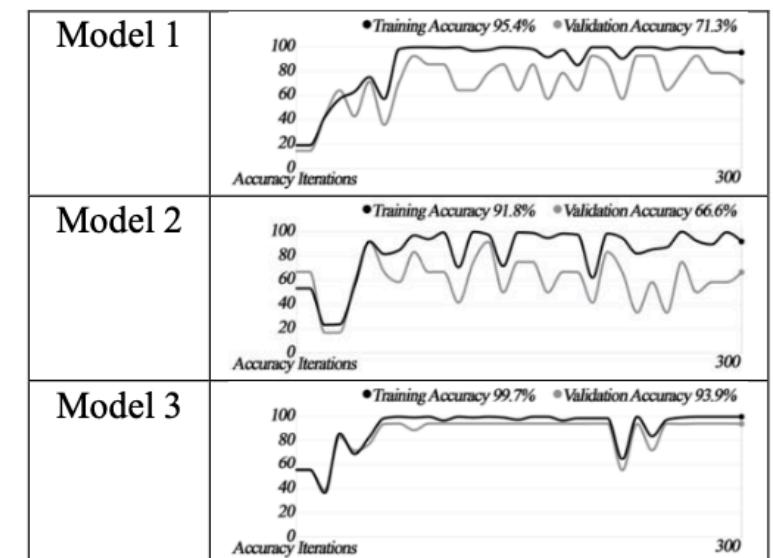
Table 2. Gesture classification by models

Model 1	raise both hands to the side raise the left hand to the side raise the right hand to the side raise the left hand forward raise the right hand forward no movement
Model 2	raise the left hand to the side raise the right hand to the side raise the left hand forward raise the right hand forward no movement
Model 3	raise both hands to the side

	raise the left hand to the side raise the right hand to the side no movement
--	--

The training accuracy of all the models was greater than 90%, although the graphs show that Models 2 and 3 found it slightly difficult to distinguish between forward and sideways movement.

Table 3. Accuracy graphs by models



3. Implementation

We had to build an iOS app to use the machine-learning model. The system in this study was implemented on an iPhone 12 Pro Max.

1 App Operation

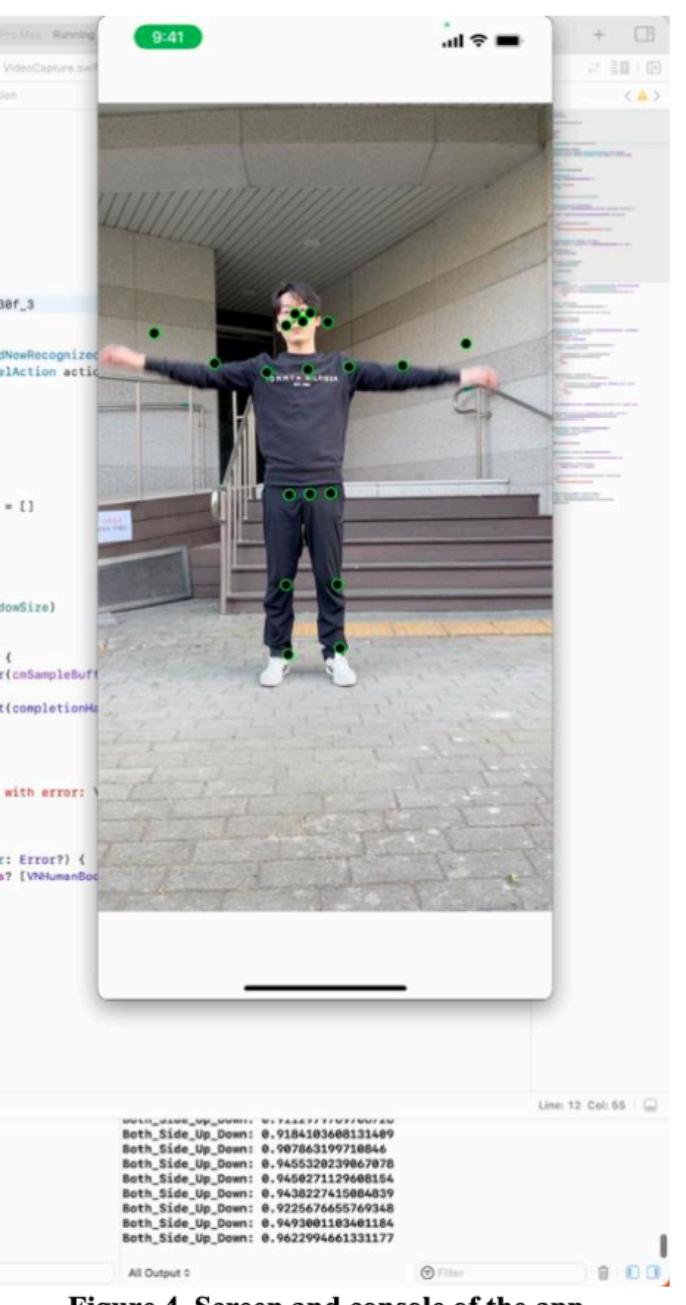


Figure 4. Screen and console of the app

2 Data Capture

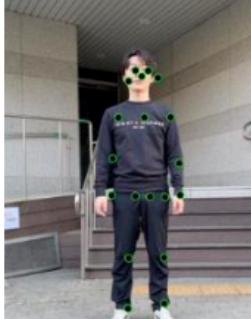
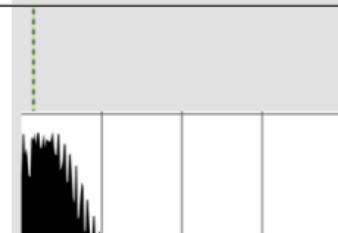
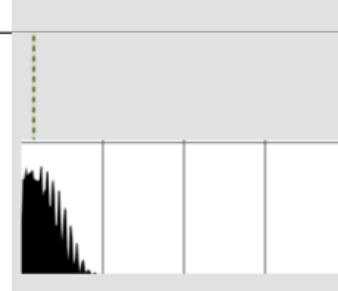
The steps in this section were as follows. The gesture was classified on the iPhone. Data identifying the gesture detected (labeled) and the correspondence rate (confidence level) via OSC⁴. Therefore, we needed to obtain the current gesture first and then send it to Max/MSP and TouchDesigner via OSC.

4. Multimedia Control

4.1 Control of Musical Instruments

We could change the instrument's timbre when we recognized a particular gesture.

Table 4. Control of musical instruments

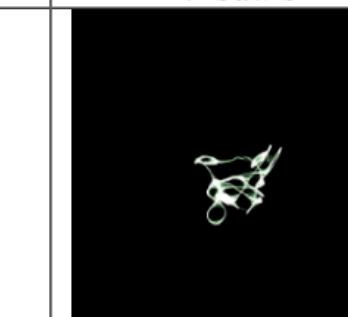
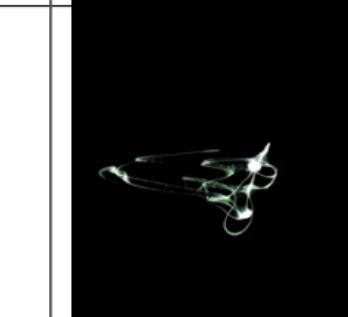
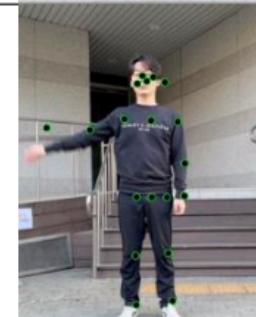
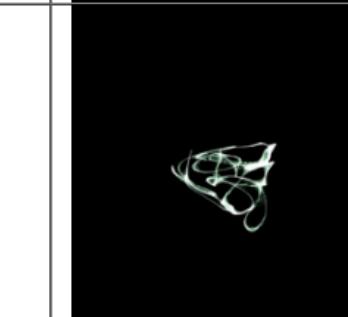
Gesture	Audio
 A photograph of a man standing with his arms at his sides. Green circular markers are placed on his head, shoulders, elbows, wrists, and hands to track his body movement.	 An empty audio spectrogram with a vertical dashed green line on the far left and four vertical gray bars representing time segments.
 A photograph of the same man raising his arms straight up from his shoulders. The green tracking markers remain in the same relative positions as in the first frame.	 An audio spectrogram showing initial activity. It features a vertical dashed green line and four vertical gray bars. A dark, jagged horizontal bar starts near the top of the frame and gradually descends towards the bottom over the course of the four time segments.
 A photograph of the man with his arms fully extended horizontally to the sides. The green tracking markers are still present on his body.	 An audio spectrogram showing a sustained signal. It features a vertical dashed green line and four vertical gray bars. A dark, jagged horizontal bar is visible across all four time segments, indicating continuous audio energy.

Open Sound Control (OSC) is a protocol for networking sound synthesizers, computers, and other multimedia devices for musical performance or show control purposes.

4.2 Control of Visuals

We could change the visuals when we recognized a particular gesture.

Table 5. Control of visuals

Gesture	Visuals
	
	
	

5. Conclusions

Currently, many interactive multimedia performances combine music, visuals, and dance, and artists make various efforts to recognize dancers' movements and gestures. Various equipment is used to create an interactive multimedia performance. We were able to use an iPhone rather than professional equipment. In addition, gestures were classified using machine learning rather than a one-to-one mapping of movements to produce more effective results.

6. References

- [1] Behringer, R. (2007, July). Gesture interaction for electronic music performance. In *International Conference on Human-Computer Interaction* (pp. 564-572). Springer, Berlin, Heidelberg.
- [2] Bhattacharya, S., Czejdo, B., & Perez, N. (2012, November). Gesture classification with machine learning using kinect sensor data. In *2012 Third International Conference on Emerging Applications of Information Technology* (pp. 348-351). IEEE.
- [3] Camurri, A., Coletta, P., Peri, M. F., Ricchetti, M., Ricci, A., Trocca, R., & Volpe, G. (2000, August). A real-time platform for interactive dance and music systems. In *ICMC*.
- [4] Chin-Shyurng, F., Lee, S. E., & Wu, M. L. (2019). Real-time musical conducting gesture recognition based on a dynamic time warping classifier using a single-depth camera. *Applied Sciences*, 9(3), 528.
- [5] Dean, T. R. (2012). *The Oxford Handbook of Computer Music*. Oxford University Press
- [6] Deng, L., Leung, H., Gu, N., & Yang, Y. (2011). Real-time mocap dance recognition for an interactive dancing game. *Computer animation and virtual worlds*, 22(2-3), 229-237.
- [7] James, J., Ingalls, T., Qian, G., Olsen, L., Whiteley, D., Wong, S., & Rikakis, T. (2006, October). Movement-based interactive dance performance. In *Proceedings of the 14th ACM international conference on Multimedia* (pp. 470-480).

[8] Nakra, T. M., & Paradiso, J. A. (1997, September). The Digital Baton: a Versatile Performance Instrument. In *ICMC*.

[9] Nakra, T. M., & Picard, R. W. (1998, December). The "conductor's jacket": A device for recording expressive musical gestures. In *ICMC*.

[10] Nakra, T. M., Ivanov, Y., Smaragdis, P., & Ault, C. (2009, June). The UBS Virtual Maestro: an Interactive Conducting System. In *NIME* (pp. 250-255).

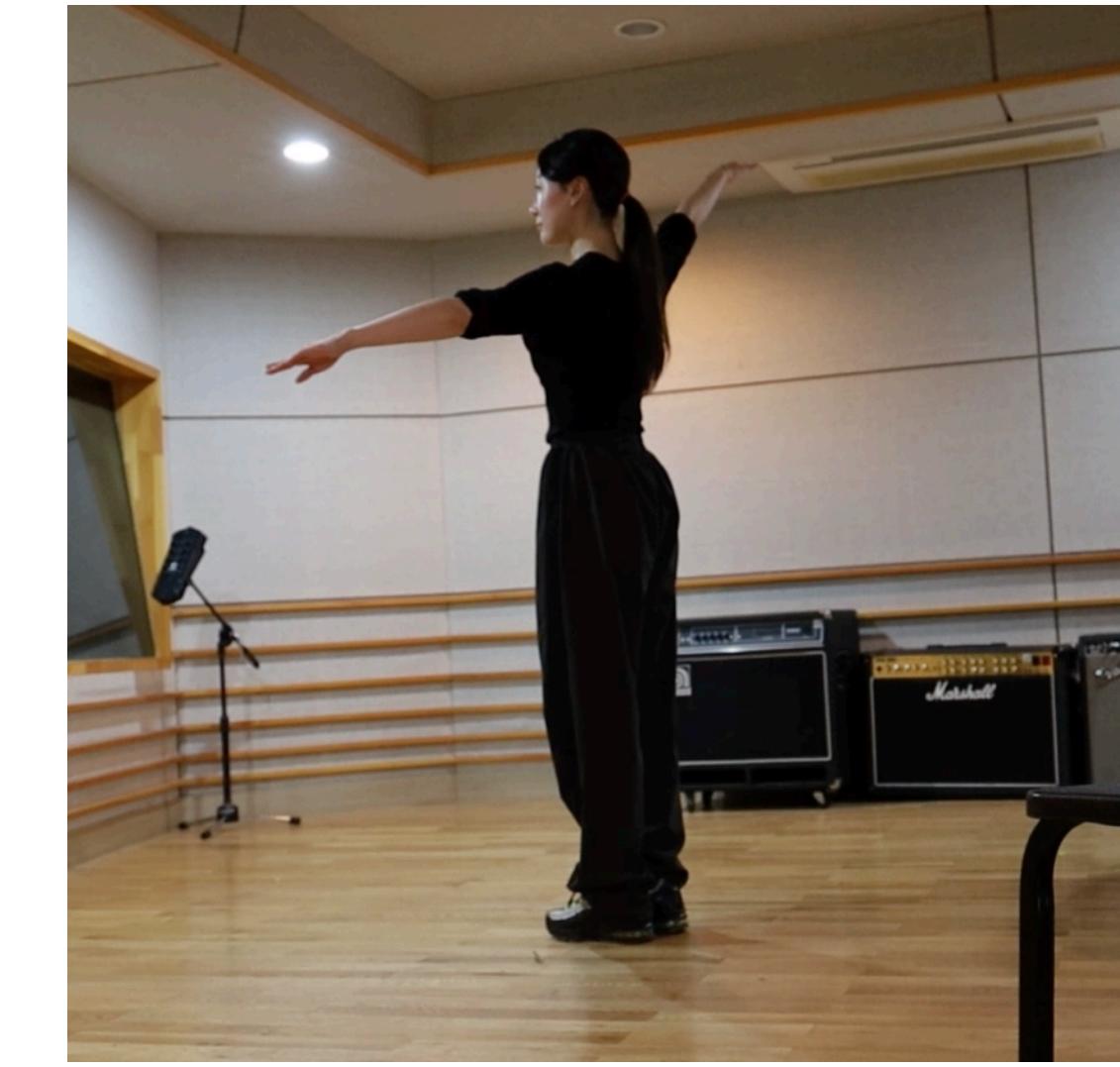
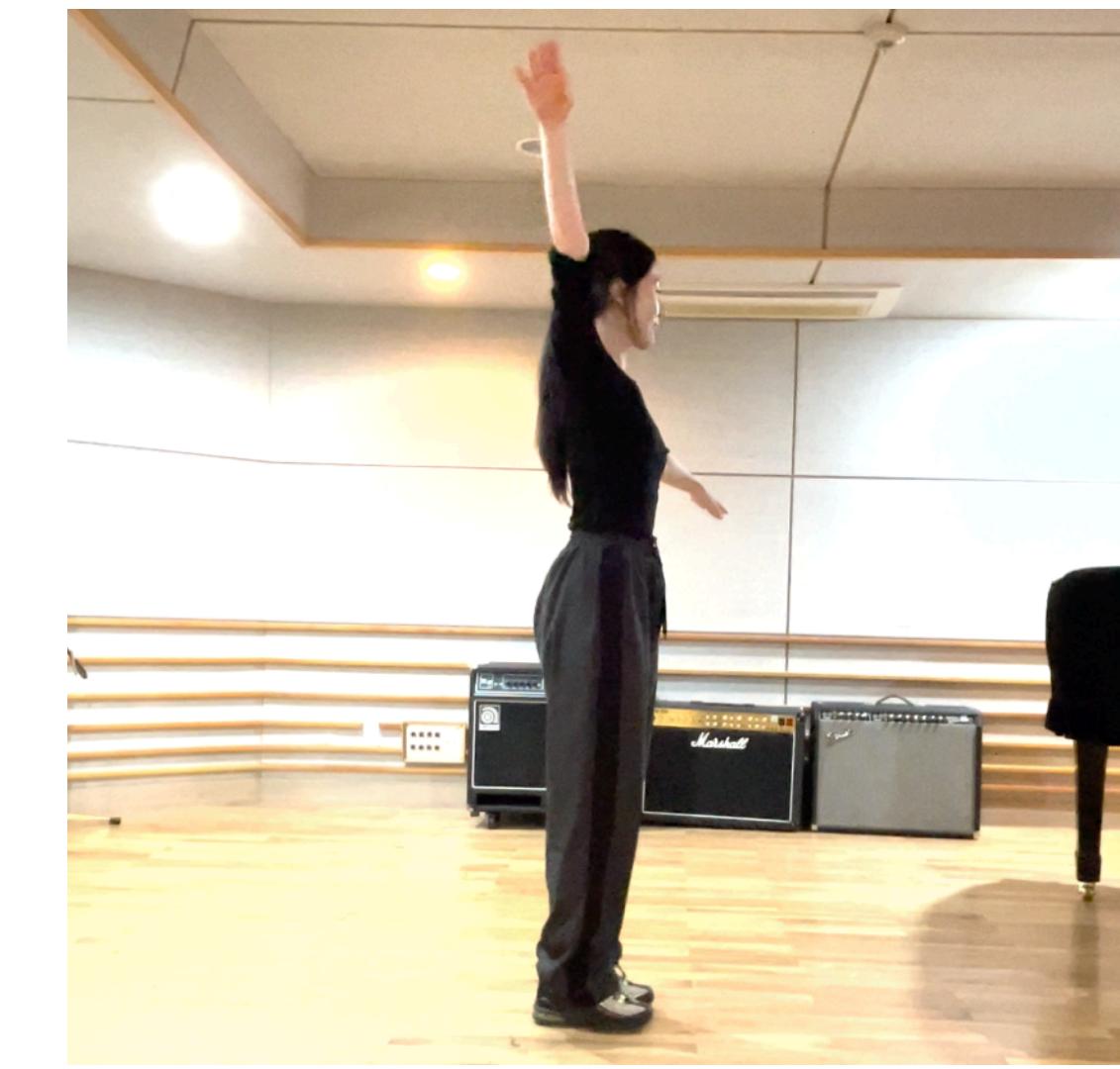
[11] Nakra, T. M. (2014). Interactive conducting systems overview and assessment. *The Journal of the Acoustical Society of America*, 135(4), 2377-2377.

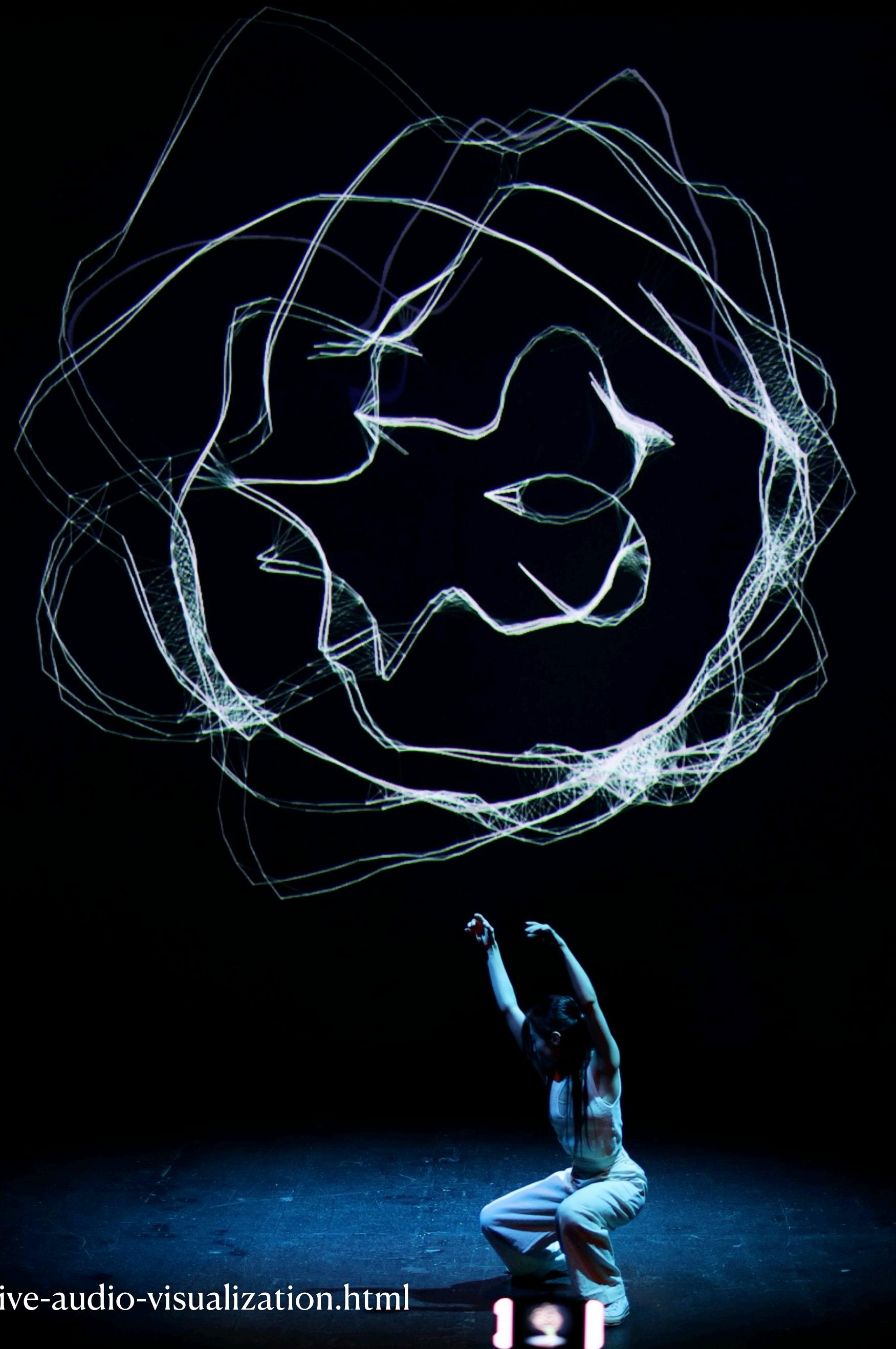
[12] Paradiso, J., & Sparacino, F. (1997). Optical tracking for music and dance performance. *Optical 3-D Measurement Techniques IV*, 11-18.

[13] Raptis, M., Kirovski, D., & Hoppe, H. (2011, August). Real-time classification of dance gestures from skeleton animation. In *Proceedings of the 2011 ACM SIGGRAPH/Eurographics symposium on computer animation* (pp. 147-156).

[14] <http://waynesiegel.dk/wp-content/uploads/2013/08/Sisters.pdf>
Accessed 26 June 2021

[15] http://waynesiegel.dk/wp-content/uploads/2013/08/Movement_Study.pdf
Accessed 26 June 2021





<https://www.gwangyulee.com/2022/11/decimalinteractive-audio-visualization.html>