See and Listen: Score-informed Association of Sound Tracks to Players in Chamber Music Performance Videos

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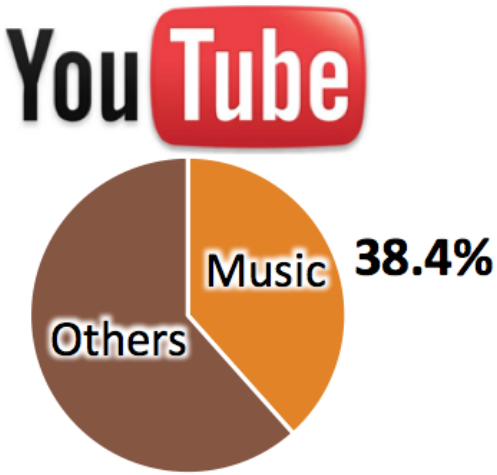
Background

- Music → Multi-modal art form
- See and listen → More enjoyment
- Popular music video streaming service

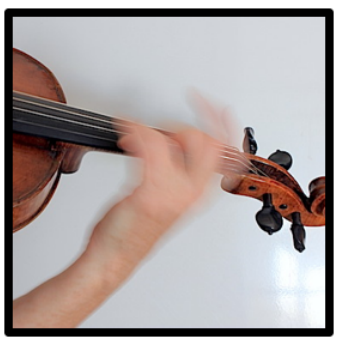


Background

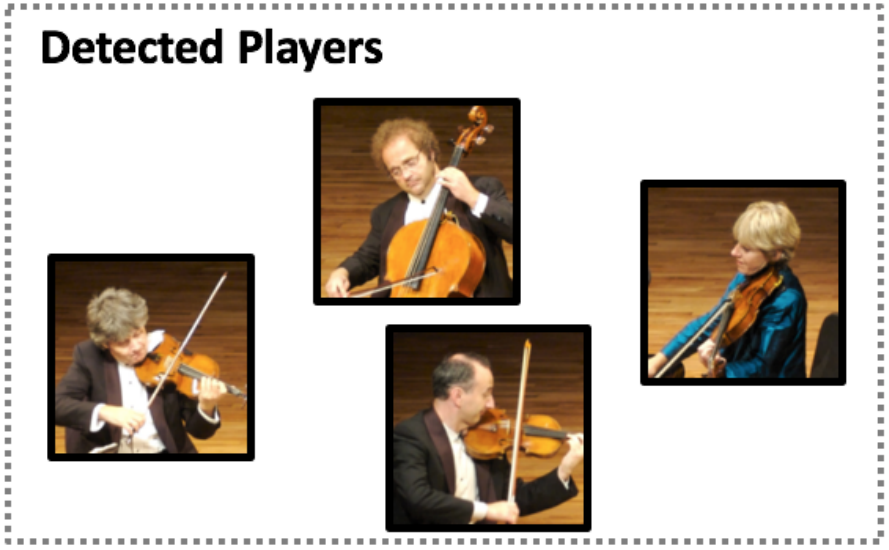
Multi-modal Music Information Retrieval

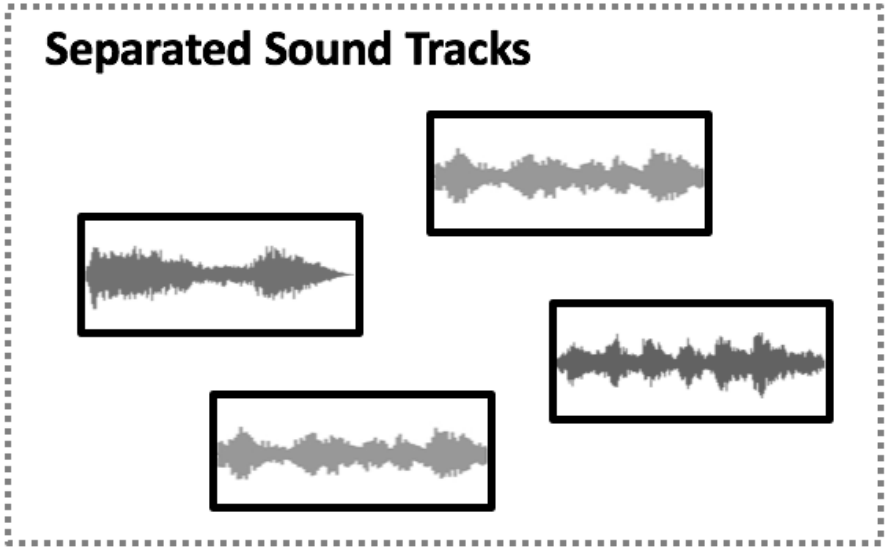
- Instrument Recognition
- Playing Activity Detection
- Polyphonic Music Analysis
- Fingering Investigation
- Conductor Following



Source Association





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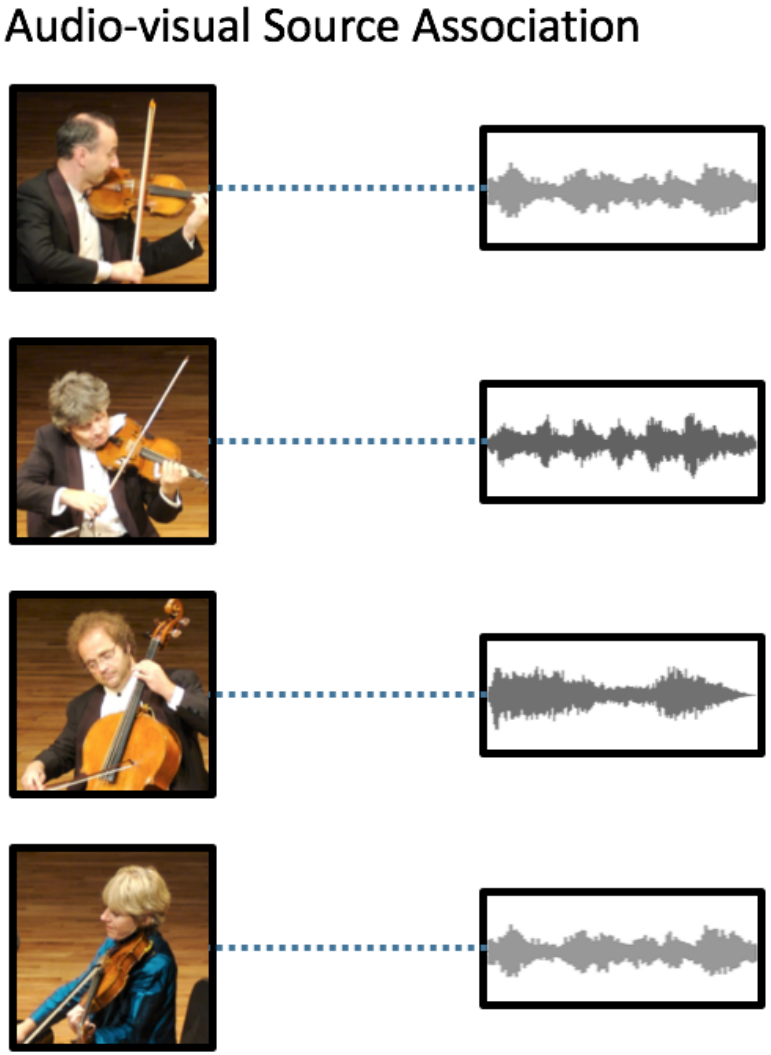

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Applications

- Intuitive and user-friendly interaction with music performance videos
- Smart Music Editor

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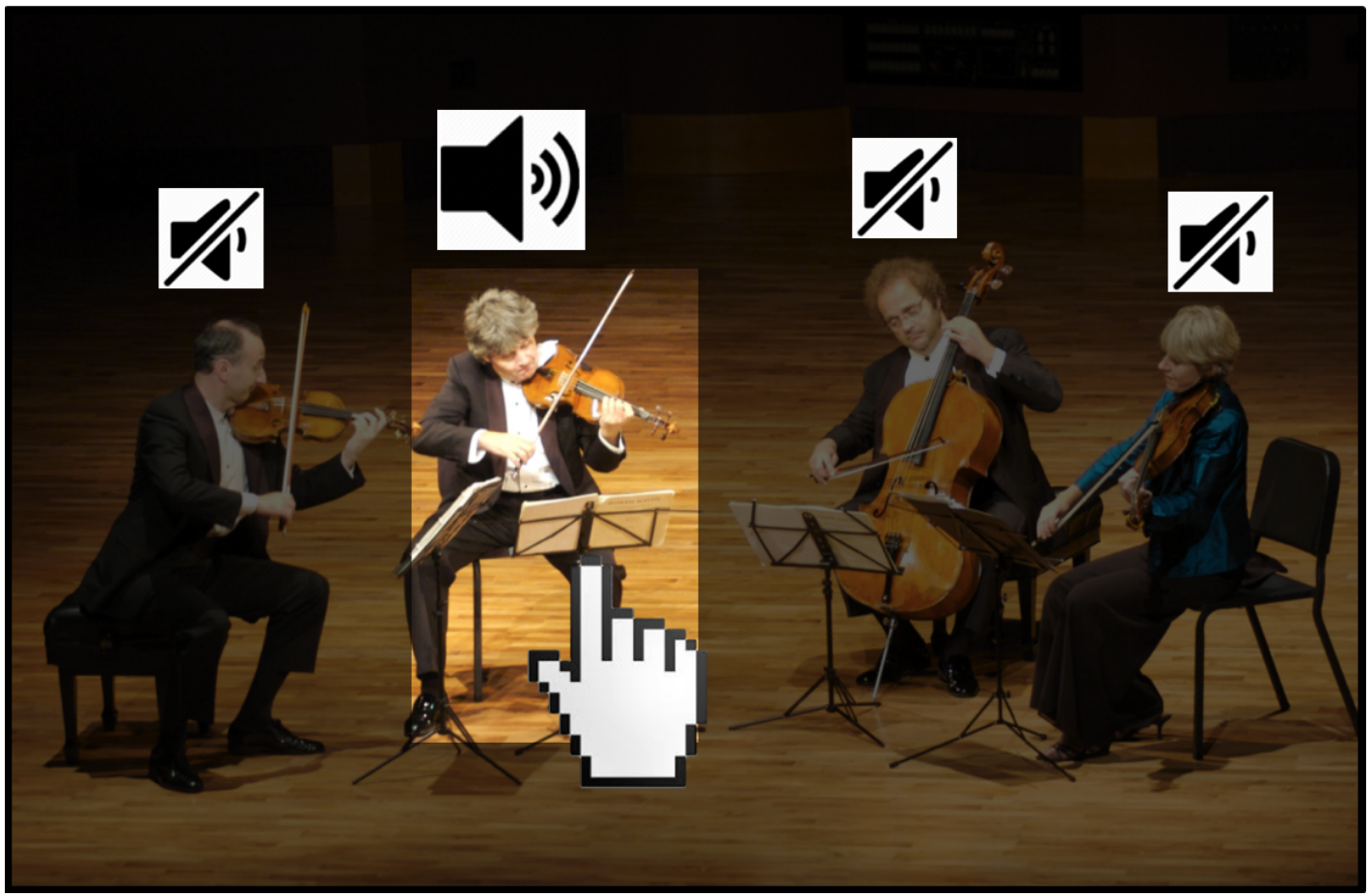

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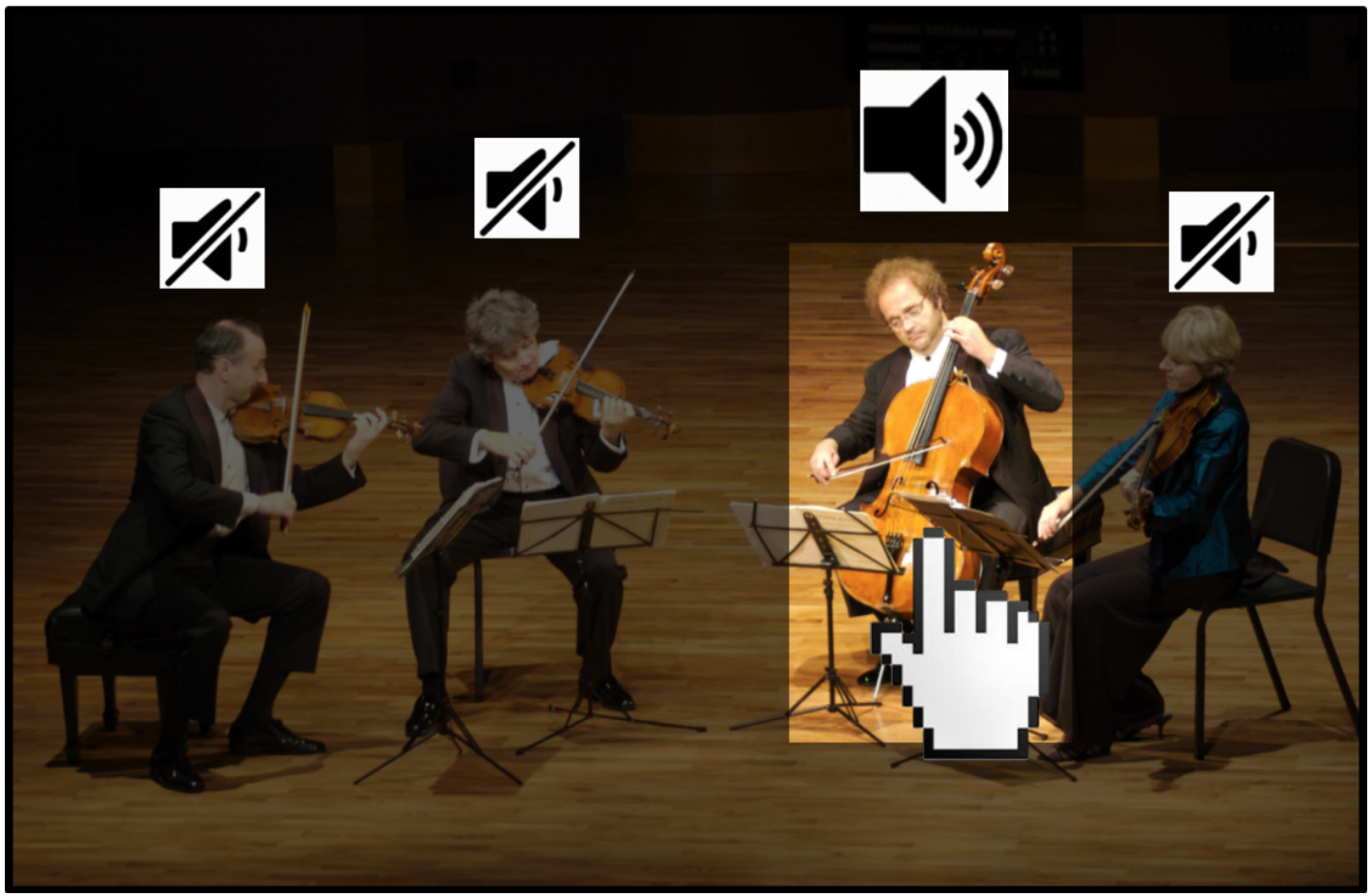
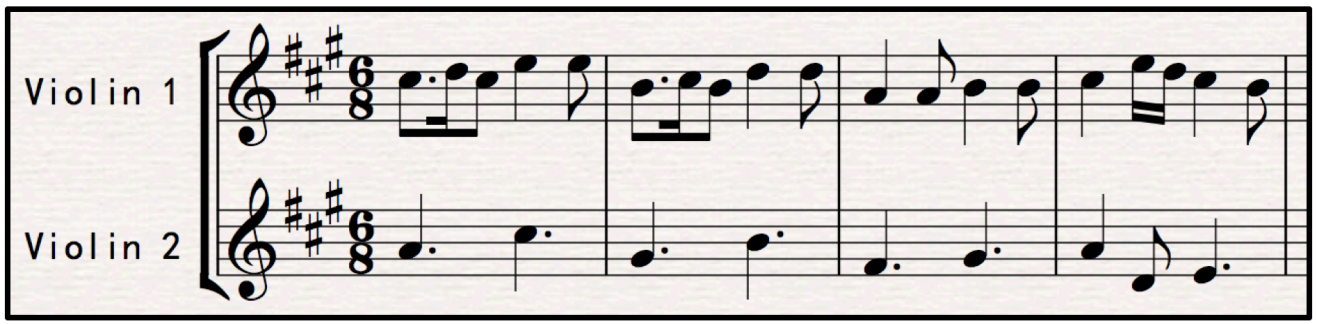
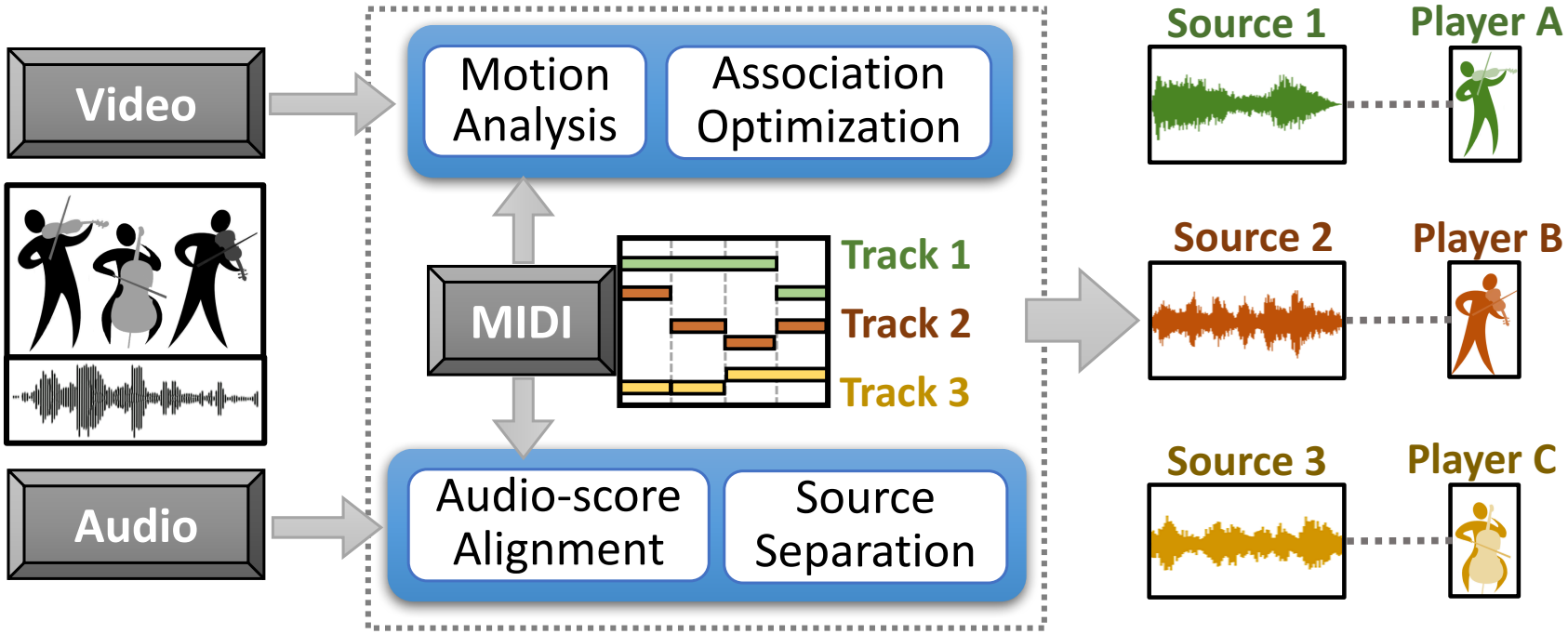


System Overview

Example:



System Overview

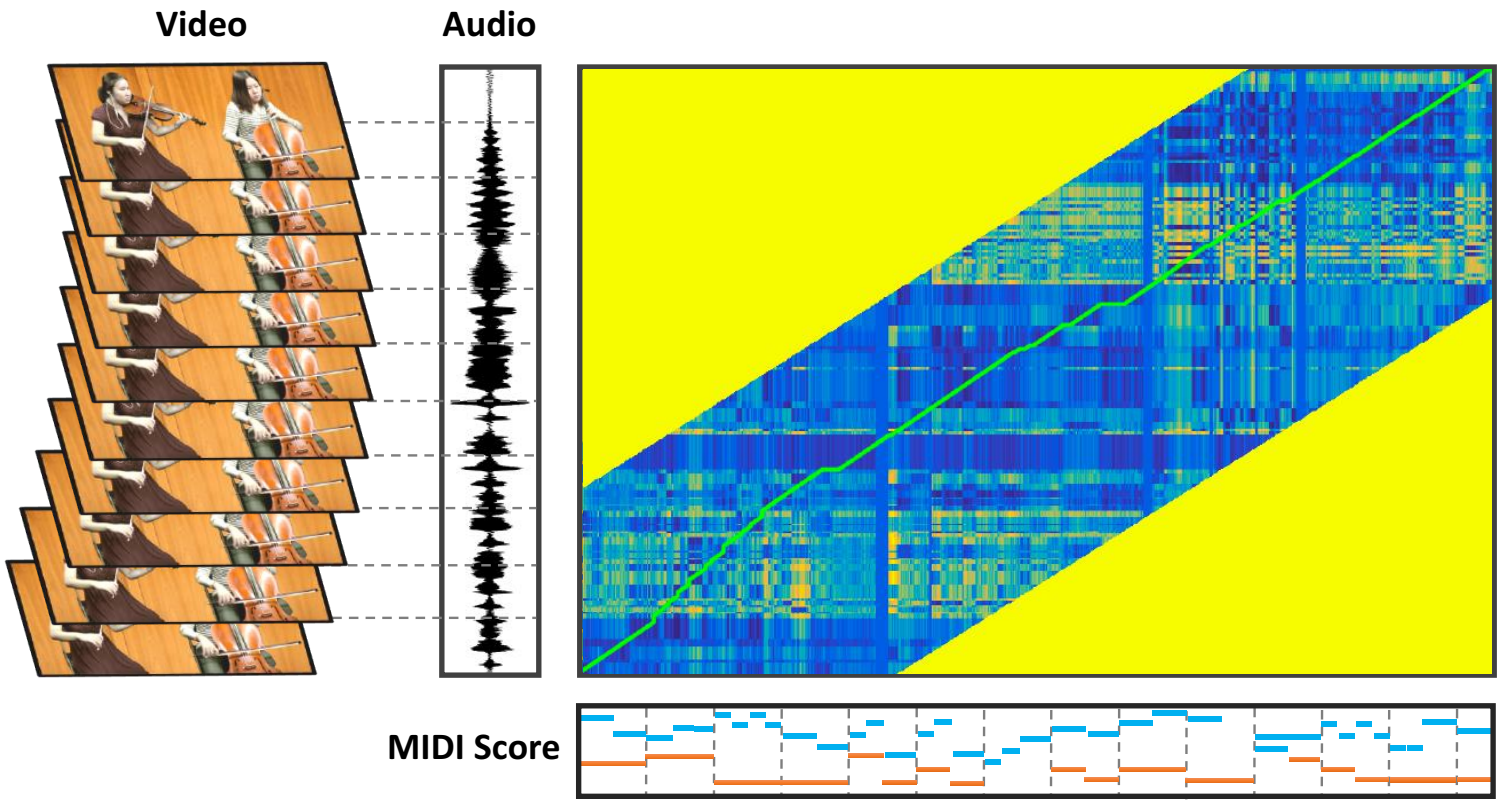


- Score-informed
- String-instruments
- Bow stroke $\Rightarrow$ audio event
- Correlate bow strokes with audio onsets

- Method: Audio Analysis
  - Audio-score Alignment
- Method: Video Analysis
  - Optical Flow Estimation
  - Player Detection
  - Bowing Motion Capturing
- Method: Association Optimization
- Experiments
  - Dataset
  - Evaluation Measure
  - Results

Method: Audio Analysis

Audio-score Alignment



- Chroma Feature & Dynamic Time Warping
- Video-score Alignment

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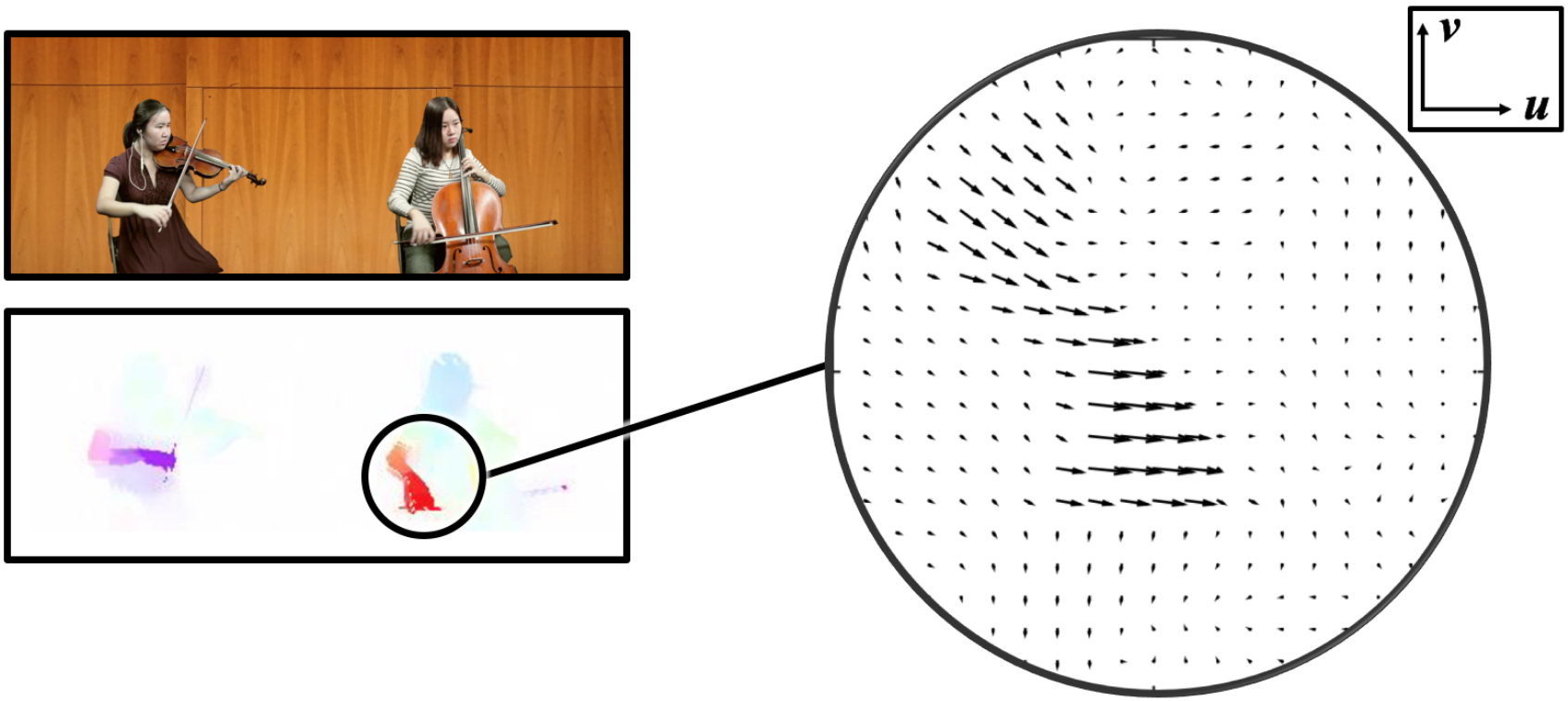
Method: Video Analysis

Optical Flow Estimation

The motion velocity of each pixel between two adjacent frames

Method: Sun et al. [2]

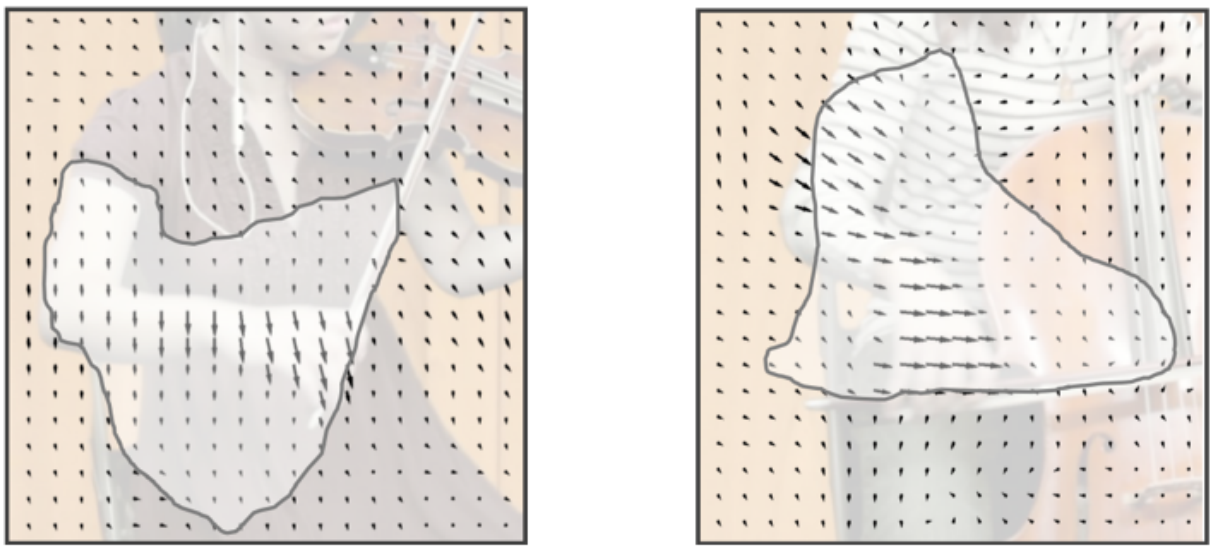


[2] D. Sun, S. Roth, and M. J. Black, Secrets of optical flow estimation and their principles, in Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR), 2010.

Method: Video Analysis

Player Detection

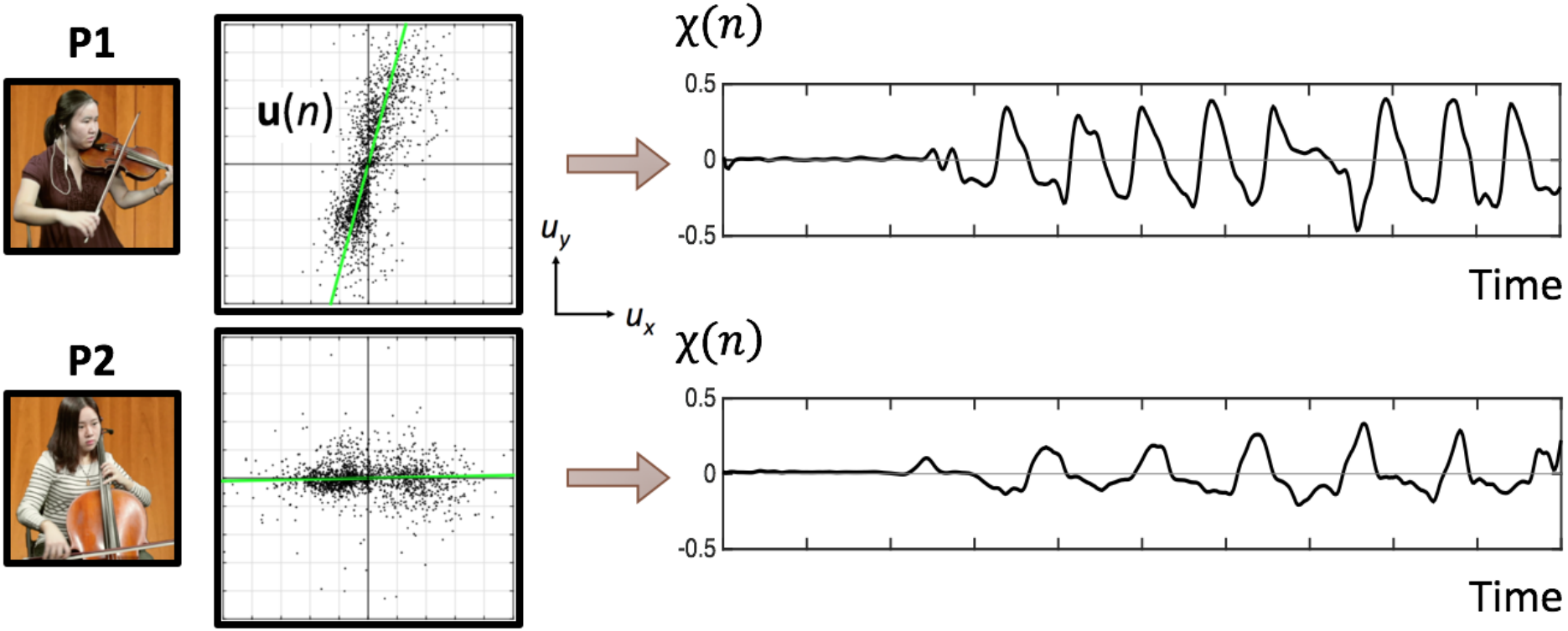
- Flow Magnitude ⇒ GMM Clustering ⇒ Player Region
- Thresholding ⇒ High Motion Region



Method: Video Analysis

Bowing Motion Capturing

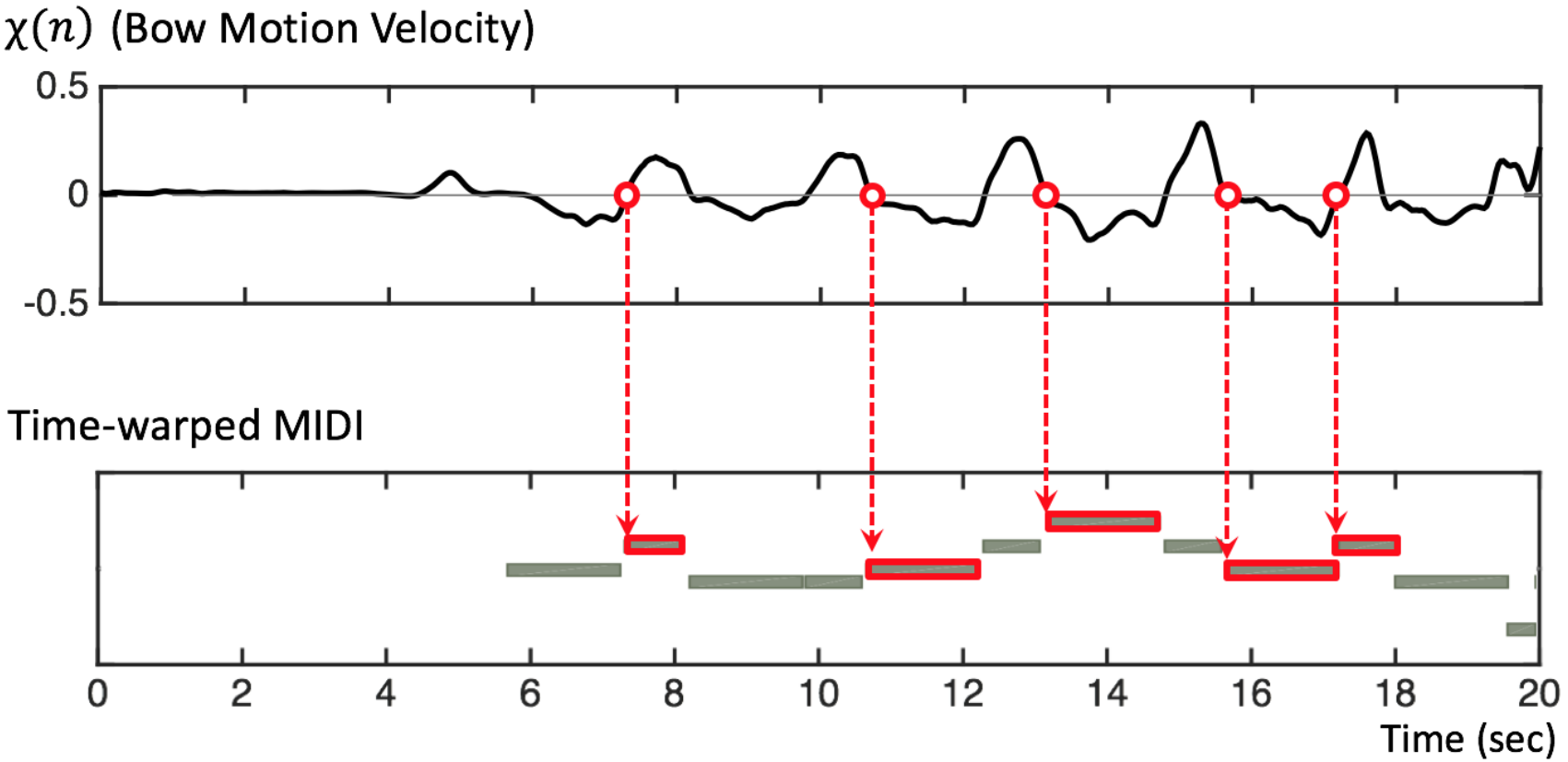
- Frame-wise global motion vector $\Rightarrow \mathbf{u}(n) = [u_x(n), u_y(n)]^T$.
- Principal component analysis (PCA) $\Rightarrow \tilde{\mathbf{u}} = (\tilde{u}_x, \tilde{u}_y)^T$
- Dimension reduction $\Rightarrow \chi(n) = \frac{\mathbf{u}(n)^T \tilde{\mathbf{u}}}{\|\tilde{\mathbf{u}}\|}$



Method: Video Analysis

Bowing Motion Capturing

Correlation:



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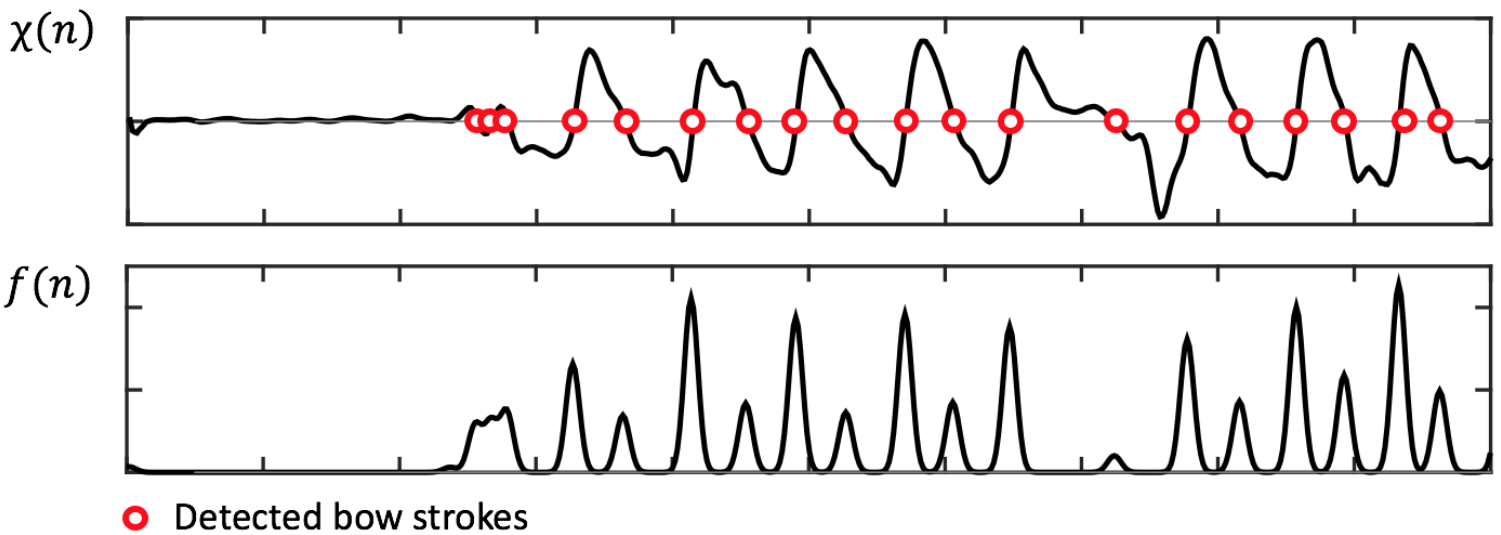
Method: Association Optimization

Pair-wise Matching

Bow Onset Likelihood:

$$f(n) = \left(\sum_{m \in \mathcal{Z}} \bar{\chi}(m) \cdot \delta(n, m) \right) * \mathcal{N}(0, \sigma^2) \tag{1}$$

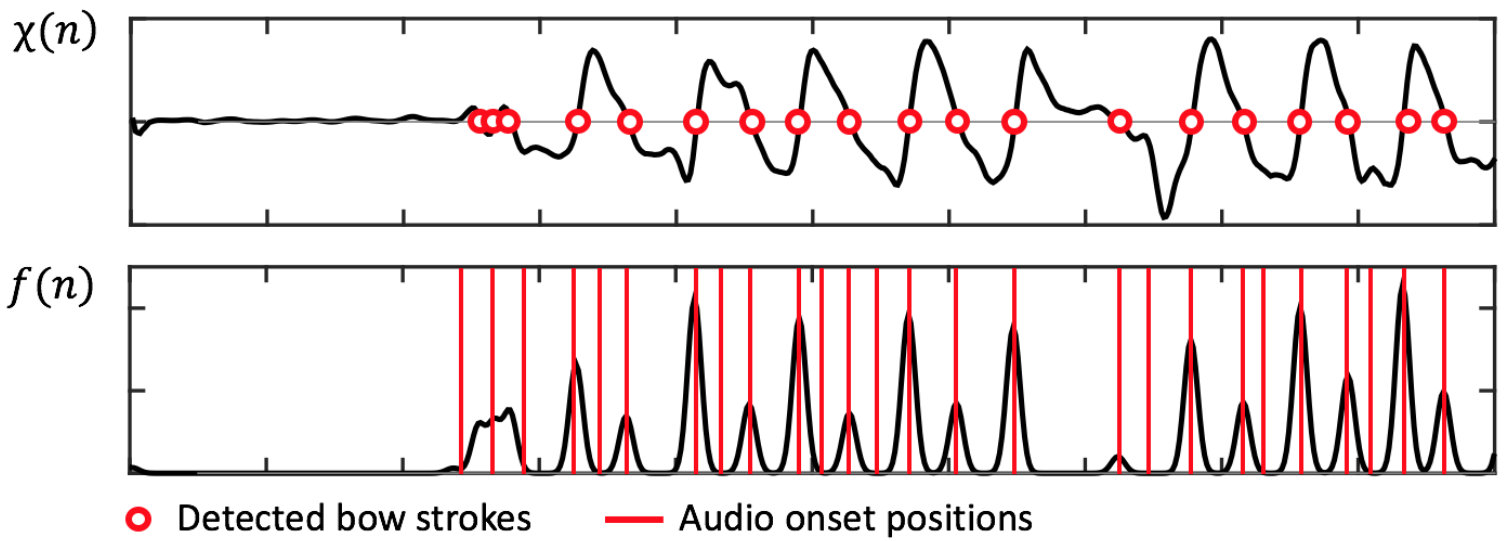


Method: Association Optimization

Pair-wise Matching

Bow Onset Likelihood:

$$f(n) = \left(\sum_{m \in \mathcal{Z}} \bar{\chi}(m) \cdot \delta(n, m) \right) * \mathcal{N}(0, \sigma^2) \tag{2}$$

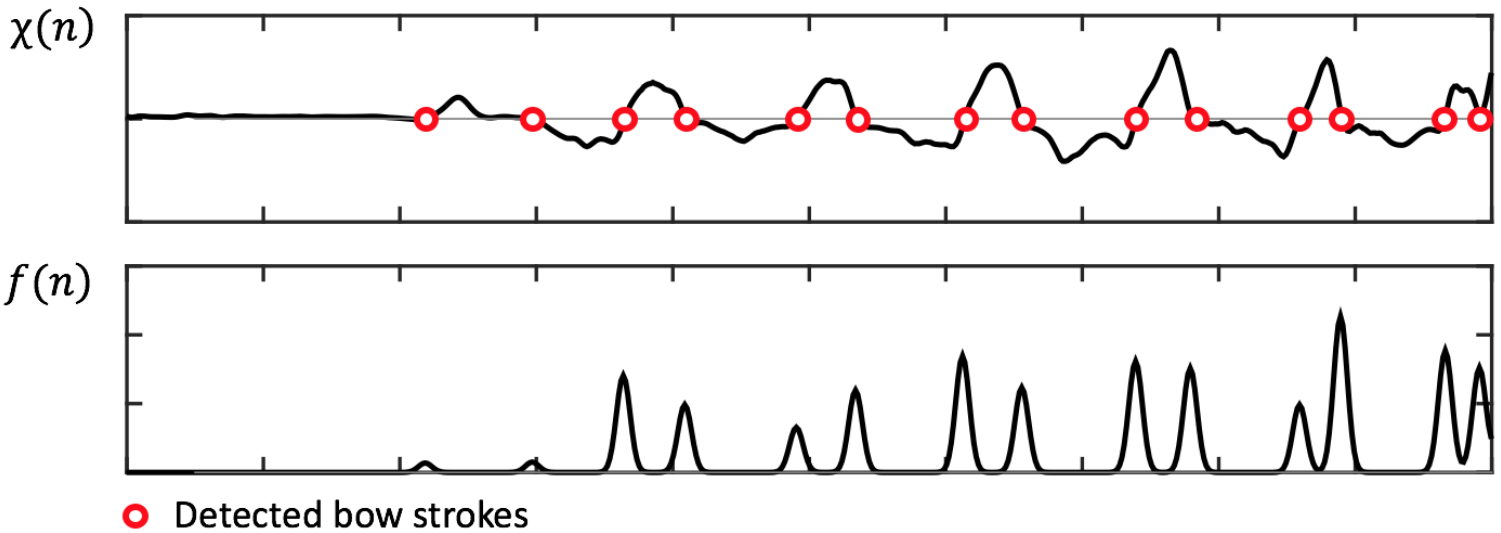


Method: Association Optimization

Pair-wise Matching

Bow Onset Likelihood:

$$f(n) = \left(\sum_{m \in \mathcal{Z}} \bar{\chi}(m) \cdot \delta(n, m) \right) * \mathcal{N}(0, \sigma^2) \tag{3}$$



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Pair-wise Matching

Bow Onset Likelihood:

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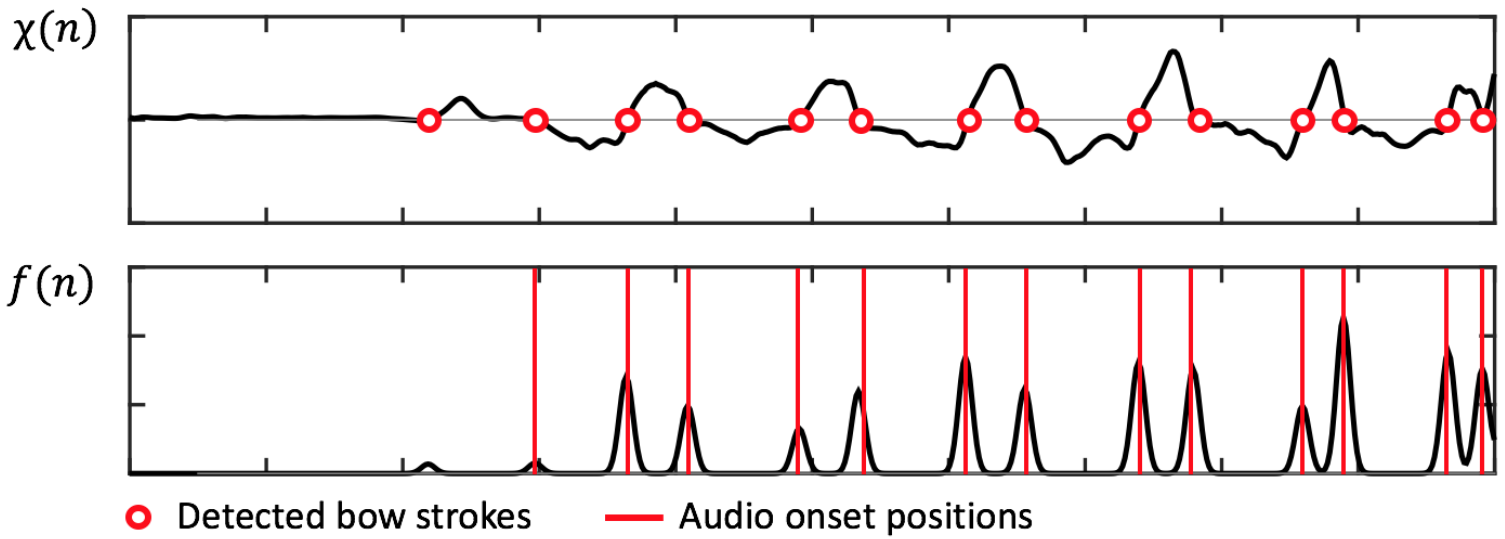


Method: Association Optimization

Matching Function:

$$\begin{cases} M^{-}_{p,q} = f_p(n)^T g_q(n) / \sum_m g_q(m) \\ M^{+}_{p,q} = f_p(n)^T g_q(n) / \sum_m f_p(m) \\ M_{p,q} = \sqrt{M^{-}_{p,q} \cdot M^{+}_{p,q}}, \end{cases} . \tag{5}$$

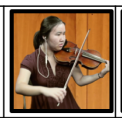
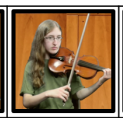
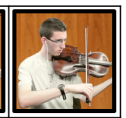
- $f_p(n) \rightarrow$ Bow onset likelihood for the p-th player.
- $g_q(n) \rightarrow$ Onset sequence for q-th track.
- $M^{-}_{p,q}$: This is low for legato bowing
- $M^{+}_{p,q}$: This is low for non-related body motion.

Method: Association Optimization

Association Score:

$$S_\sigma = \prod_{p=1}^{N} M_{p,\sigma(p)} \tag{6}$$

- For N players/tracks $\rightarrow$ N! bijections.
- $\sigma(\cdot) \rightarrow$ Permutation function.
- Select σ that maximizes S_σ.

				
♫	$M_{1,1}$	$M_{2,1}$	$M_{3,1}$	$M_{4,1}$
♫	$M_{1,2}$	$M_{2,2}$	$M_{3,2}$	$M_{4,2}$
♫	$M_{1,3}$	$M_{2,3}$	$M_{3,3}$	$M_{4,3}$
♫	$M_{1,4}$	$M_{2,4}$	$M_{3,4}$	$M_{4,4}$

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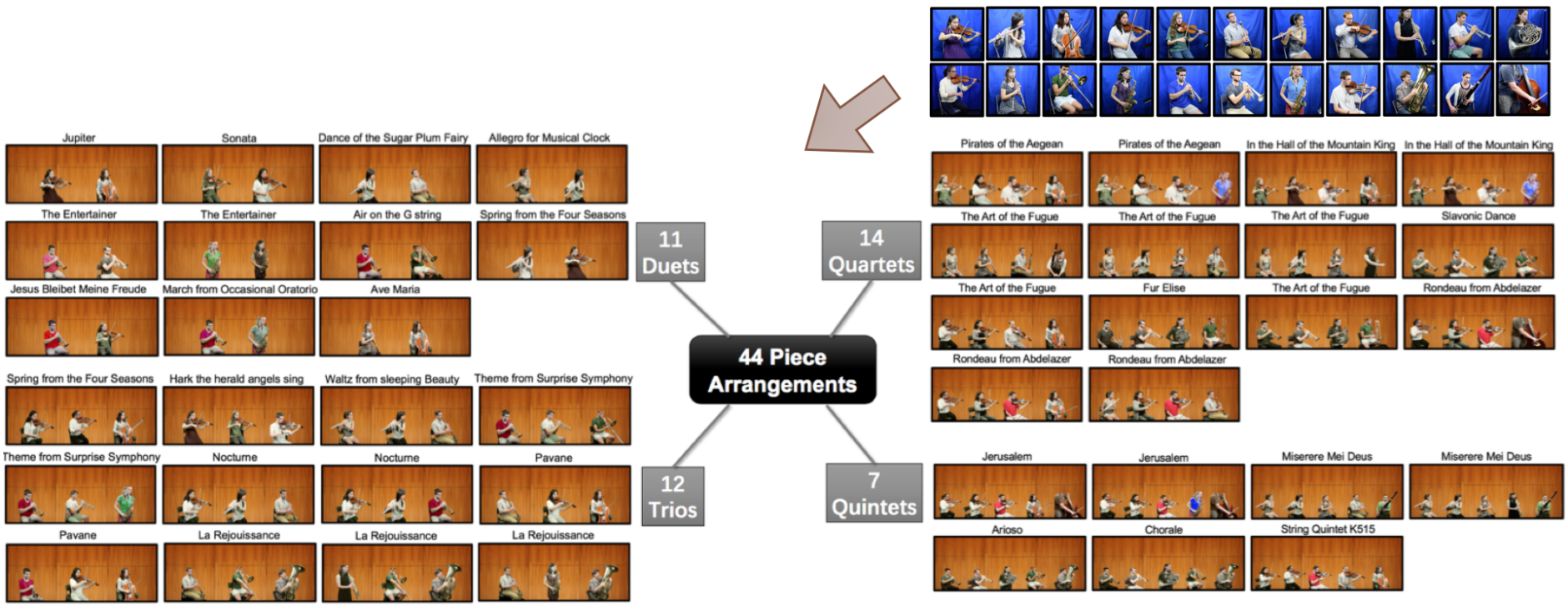
Experiments

Dataset: URMP Dataset [3]

- 14 instruments, 44 piece arrangements
- Individually recorded and assembled together



[3] B. Li *, X. Liu *, K. Dinesh, Z. Duan, and G. Sharma, Creating a musical performance dataset for multimodal music analysis: Challenges, insights, and applications, IEEE Trans. Multimedia, under review. (* Equal Contribution)

Experiments

Piece Selection

- We select 19 pieces $\rightarrow$ 5 duets, 4 trios, 7 quartets, 3 quintets
- Selection criteria: contains at most 1 non-string instrument

Overall Results

- Piece-level success rate: 89.5% (17 of 19 pieces)

** All sources within one piece should be correctly associated*

- Source-level success rate: 89.2% (58 of 65 sources)

Piece-wise Evaluation Measure

- Association Rank: the association score rank of the ground-truth association
- Metric Ratio: the ratio between the association score of the ground-truth association and the highest competitive one

Experiments

Piece-wise Results

Metadata				Association Measures		
No.	Instrument Type	Piece Length (mm:ss)	Polyphony - (No. permutations)	No. of Correctly Associated Sources	Rank of Correct Association	Metric Ratio
1	Vn. Vc.	01:03	2 - (2)	2	1	1.454
2	Vn1. Vn2.	00:46	2 - (2)	2	1	1.689
3	Fl. Vn.	00:35	2 - (2)	2	1	1.036
4	Tp. Vn.	03:19	2 - (2)	2	1	3.203
5	Ob. Vc.	01:44	2 - (2)	2	1	2.519
6	Vn1. Vn2. Vc.	02:12	3 - (6)	3	1	1.821
7	Vn1. Vn2. Va.	00:47	3 - (6)	3	1	1.048
8	Cl. Vn. Vc.	02:13	3 - (6)	3	1	1.247
9	Tp. Vn. Vc.	02:13	3 - (6)	3	1	1.289
10	Vn1. Vn2. Va. Vc.	00:50	4 - (24)	4	1	1.470
11	Vn1. Vn2. Va. Sax.	00:50	4 - (24)	4	1	1.142
12	Vn1. Vn2. Va. Vc.	01:25	4 - (24)	4	1	1.138
13	Vn1. Vn2. Va. Sax.	01:25	4 - (24)	2	5	0.769
14	Vn1. Vn2. Va. Vc.	02:54	4 - (24)	4	1	9.106
15	Vn1. Vn2. Va. D.B.	02:08	4 - (24)	4	1	1.330
16	Vn1. Vn2. Va. Vc.	02:08	4 - (24)	4	1	1.281
17	Vn1. Vn2. Va. Vc. D.B.	01:59	5 - (120)	5	1	1.438
18	Vn2. Vn2. Va. Sax. D.B.	01:59	5 - (120)	5	1	1.135
19	Vn1. Vn2. Va1. Va2. Vc.	03:45	5 - (120)	0	19	0.564

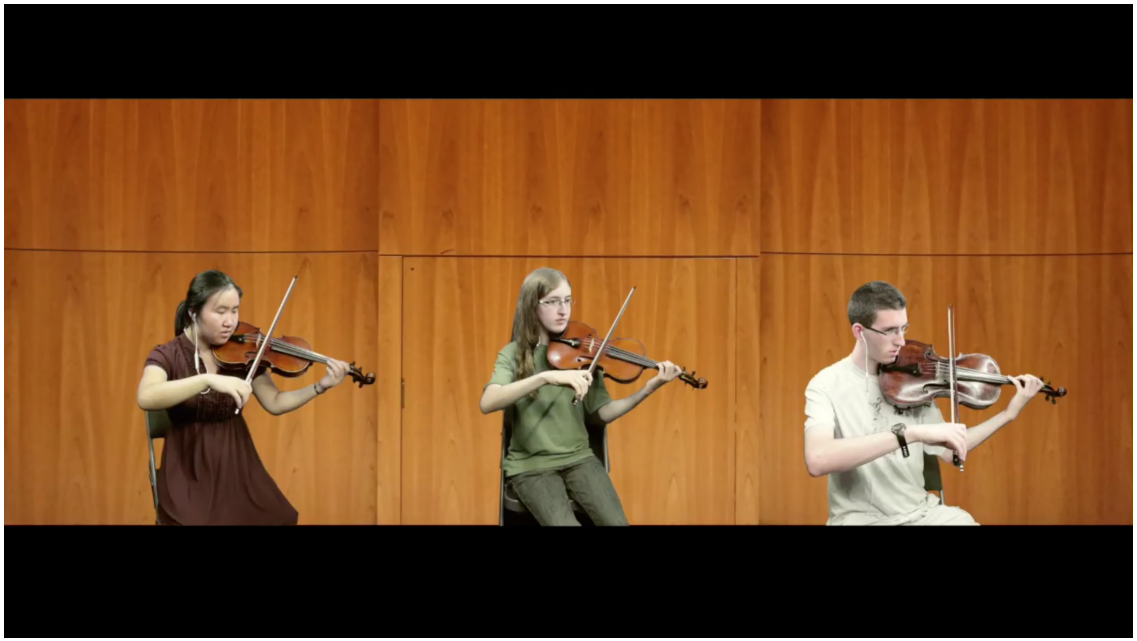
Failure case investigations:

- Non-string instrument $\rightarrow$ Motions not correlated
- Legato bowing $\rightarrow$ Audio onsets not correlated
- Same rhythmic patterns $\rightarrow$ Difficult to identify

Video

- Legato bowing

- Same rhythmic patterns



Conclusion

- Methodology for audio-visual source association
- High success rate
- Richer music enjoyment experiences