

Extended playing techniques: the next milestone in musical instrument recognition

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ABSTRACT

The expressive variability in which a musical note can be produced conveys some essential information to the modeling of orchestration and style. Yet, although the automatic recognition of a musical instrument from the recording of a single “ordinary” note is now considered a solved problem, the ability of a computer to precisely identify instrumental playing techniques (IPT) remains largely underdeveloped. In this paper, we conduct a benchmark of machine listening systems for query-by-example browsing among 143 instrumental playing techniques, including the most contemporary, for 16 instruments in the symphonic orchestra, thus amounting to 469 triplets of instrument, mute, and technique. We identify and discuss three necessary conditions for significantly outperforming the classical mel-frequency cepstral coefficients (MFCC) baseline: the inclusion of second-order scattering coefficients to account for the presence of amplitude modulations; the inclusion of long-range temporal dependencies; and the resort to large-margin nearest neighbors (LMNN), a supervised metric learning method that reduces intra-class variability in feature space. We report a P@5 of 99.7% for instrument recognition (baseline at 89.0%) and of 61.0% for playing technique recognition (baseline at 44.5%). We interpret this quantitative gain by means of a qualitative assessment of practical usability as well as data visualizations resulting from nonlinear dimensionality reduction.

CCS CONCEPTS

- Computer systems organization → Embedded systems; Redundancy; Robotics;
- Networks → Network reliability;

KEYWORDS

ACM proceedings, L^AT_EX, text tagging

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1 INTRODUCTION

The gradual diversification of the timbral palette in Western classical music at the turn of the 20th century is reflected in five concurrent trends: the addition of new instruments to the symphonic instrumentarium, either by technological inventions (e.g. theremin) or importation from non-Western musical cultures (e.g. marimba) [49, epilogue]; the creation of novel instrumental associations, as epitomized by *Klangfarbenmelodie* [50, chapter 22]; the temporary alteration of resonant properties through mutes and other “preparations” [16]; a more systematic usage of extended instrumental techniques, such as artificial harmonics, *col legno batutto*, or flutter tonguing [29, chapter 11]; and the resort to electronics and digital audio effects [59]. The first of these trends has somewhat stalled: to this day, most Western composers rely on an acoustic instrumentarium that is only marginally different from the one that was available in the Late Romantic period. Nevertheless, the latter approaches to timbral diversification were massively adopted into post-war contemporary music. In particular, an increased concern for the concept of musical gesture [22] has liberated many unconventional instrumental techniques from their figurativistic connotations, thus making the so-called “ordinary” playing style merely one of many compositional – and improvisational – options.

Far from being exclusive to erudite music, extended playing techniques are also commonly found in oral tradition; in some cases, they even stand out as a distinctive component of musical style. Four well-known examples are: the snap pizzicato (“slap”) of the upright bass in rockabilly, the growl of the tenor saxophone in rock’n’roll, the shuffle stroke of the violin (“fiddle”) in Irish folklore, and the glissando of the clarinet in Klezmer music. Consequently, the mere knowledge of organology (the instrumental *what?* of music), as opposed to chironomics (its gestural *how?*), is a rather weak source of information for browsing and recommendation in large music databases.

Yet, past research in music information retrieval (MIR), and especially machine listening, rarely acknowledges the benefits of integrating the influence of performer gestures into a coherent taxonomy of musical instrument sounds. Instead, gestures are either framed as a spurious form of intra-class variability between instruments, without delving into its interdependencies with pitch and intensity; or, symmetrically, as a probe for the acoustical study of a given instrument, without enough emphasis onto the broader picture of orchestral diversity.

One major cause of this gap in research is the difficulty of collecting and annotating data for contemporary instrumental techniques. Fortunately, such obstacle has recently been overcome, owing to the creation of databases of instrumental samples in a perspective

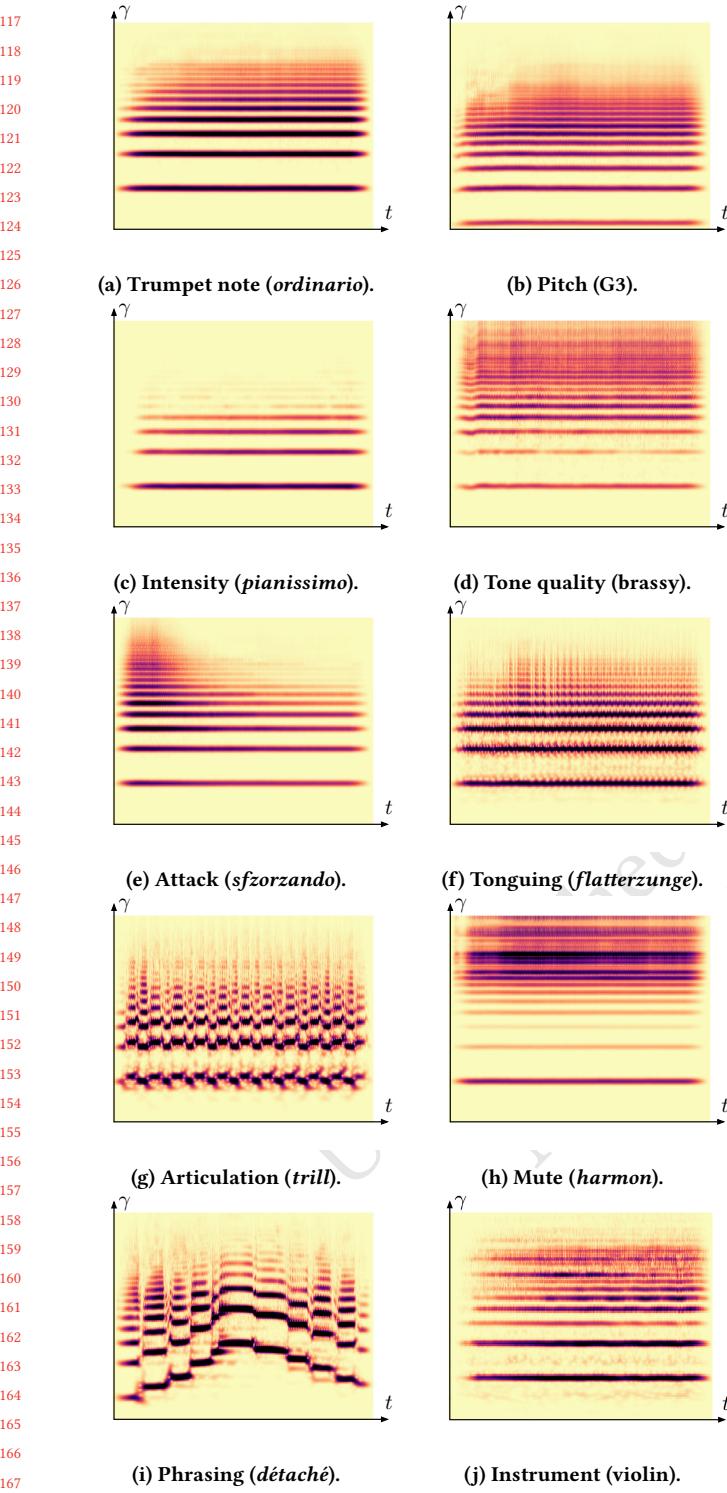


Figure 1: Ten factors of variations of a musical note.

of spectralist music orchestration [39]. In this article, we capitalize on the availability of data to formulate a new line of research in MIR, namely the joint retrieval of organological information (“*what* instrument is being played in this recording?”) and chironomical information (“*how* is the musician producing sound?”), while remaining invariant to other factors of variability, which are deliberately regarded as contextual: at what pitches and intensities, but also where, when, why, by whom, and for whom was the music recorded.

Figure 1a shows the constant- Q wavelet scalogram (i.e. the complex modulus of the constant- Q wavelet transform) of a trumpet musical note, as played with an ordinary technique. Unlike most existing publications on instrument classification, which exclusively focus on pitch (Figure 1b) and intensity (Figure 1c) as the main factors of intra-class variability, this paper aims at accounting for the presence of instrumental playing techniques (IPT), such as changes in tone quality (Figure 1d), attack (Figure 1e), tonguing (Figure 1f), and articulation (Figure 1h), either as intra-class variability (instrument recognition task) or as inter-class variability (IPT recognition task). The analysis of IPTs whose definition necessarily involves more than a single musical event, such as phrasing (Figure 1i), is beyond the scope of this paper.

Section 2 reviews the existing literature on the topic. Section 3 derives the task of IPT classification from the definition of both a taxonomy of instruments and a taxonomy of gestures. Section 4 describes how two topics in machine listening, namely scattering transforms and supervised metric learning, are relevant to address this task. Section 5 reports the results from an IPT classification benchmark on the Studio On Line (SOL) dataset.

2 RELATED WORK

This section reviews some of the recent MIR literature on the audio analysis of instrumental playing techniques, with a focus on the available datasets for each formulation of the problem at hand.

2.1 Classification of ordinary isolated notes

The earliest works on musical instrument recognition restricted their scope to individual notes played with an ordinary technique – with datasets such as MUMS [46], MIS, RWC [23], and Philharmonia – thus eliminating most factors of intra-class variability due to the performer [6, 11, 18, 25, 27, 40, 55]. These works have culminated with the development of a support vector machine (SVM) classifier trained on spectrotemporal receptive fields (STRF), which are idealized computational models of neurophysiological responses in the central auditory system [14]. Not only did it attain a near-perfect mean accuracy of 98.7% on the RWC dataset, but the confusion matrix of its automated predictions was closely similar to the confusion matrix of human listeners [48]. Therefore, the supervised classification of musical instruments from recordings of ordinary notes could arguably be considered a solved problem; we refer to [8] for a recent review of the state of the art.

2.2 Classification of solo recordings

One straightforward extension of the problem above is the classification of solo phrases, encompassing some variability in melody [30], for which the accuracy of STRF models is around 80% [47].

233 Since the Western tradition of solo music is essentially limited to
 234 a narrow range of instruments (e.g. piano, classical guitar, violin)
 235 and genres (sonatas, contemporary, free jazz, folk), datasets of solo
 236 phrases, such as solosDb [26], are exposed to strong biases. This is-
 237 sue is partially mitigated by the recent surge of multitrack datasets,
 238 such as MedleyDB [9], which has spurred a renewed interest in
 239 single-label instrument classification [57]. In addition, the cross-
 240 collection evaluation methodology [32] allows to prevent the risk
 241 of overfitting caused by the relative homogeneity of these small
 242 datasets in terms of artists and recording conditions [10]. To this
 243 date, the best classifier of solo recordings is a spiral convolutional
 244 network [35] trained on the Medley-solos-DB dataset [34], i.e. a
 245 cross-collection dataset which aggregates MedleyDB and solosDb
 246 following the procedure of [17]. We refer to [24] for a recent review
 247 of the state of the art.

248

249

250 251 252 2.3 Multilabel classification in polyphonic mixtures

253 Because most publicly released musical recordings are polyphonic,
 254 the generic formulation of instrument recognition as a multilabel
 255 classification task is the most appropriate for large-scale deploy-
 256 ment [12, 41]. However, it suffers from two methodological caveats:
 257 first, polyphonic instrumentation is not independent from other
 258 attributes of information, such as geographical origin, genre, or key;
 259 and secondly, the inter-rater agreement decreases with the number
 260 of overlapping sources [20, chapter 6]. Such issues are all the more
 261 troublesome that there is, to this date, no annotated dataset of poly-
 262 phonic mixtures that is diverse enough to be devoid of artist bias.
 263 The Open-MIC initiative, from the newly created Community for
 264 Open and Sustainable Music and Information Research (COSMIR),
 265 might contribute to mitigating them in the near future [42].

266

267

268 269 270 2.4 Single-instrument playing technique classification

271 Lastly, there is a growing interest for studying the role of the per-
 272 former in musical acoustics, from both perspectives of sound pro-
 273 duction and sound perception. Besides its interest in audio signal
 274 processing, this topic is connected to other disciplines, such as
 275 biomechanics and gestural interfaces [44]. The majority of the
 276 available literature focuses on the range of IPTs afforded by a sin-
 277 gle instrument: recent examples include clarinet [36], percussion
 278 [52], piano [7], guitar [13, 19, 51], violin [58], cello [15, chapter
 279 6], and erhu [56]. Some publications frame timbral similarity in
 280 a polyphonic setting, yet do so according to a purely perceptual
 281 definition of timbre – with continuous attributes such as brightness,
 282 warmth, dullness, roughness, and so forth – without connecting
 283 these attributes to the discrete latent space of IPTs [3].

284 In this paper, we formulate the retrieval of expressive parameters
 285 of musical timbre at the scale of the symphonic orchestra at large,
 286 while expliciting these parameters in terms of sound production
 287 (i.e. through a finite set of instructions, readily interpretable by the
 288 performer) rather than by means of perceptual epithets only. We
 289 refer to [31] for a recent review of the state of the art.

290

3 TASKS

In this section, we distinguish taxonomies of musical instruments from taxonomies of musical gestures.

3.1 Taxonomies

The Hornbostel-Sachs taxonomy (H-S) strives to organize the diversity of musical instruments according to their manufacturing characteristics only, and is purposefully unaffected by sociohistorical background [45]. Because it offers an unequivocal way of describing any acoustic instrument without any prior knowledge on its applicable IPTs, it serves as a *lingua franca* in ethnomusicology and museology, especially for ancient or rare instruments which may lack available informants. The location of the violin in H-S (321.321-71), as depicted in Figure 2, also encompasses the viola and the cello in addition to the violin. This is because these three instruments, viewed as inert objects, share a common morphology, despite differences in posture for the performer: both violin and viola are usually played under the jaw whereas the cello is held between the knees. Accounting for these differences begs to refine H-S by means a vernacular taxonomy. Most instrument taxonomies in music signal processing, including MedleyDB and AudioSet [21], reach the vernacular level rather than conflating all instruments belonging to the same H-S node. In some cases, an even finer level of granularity is attained by the listing of potential alterations to the instrument – be them permanent or temporary, at the time scale of more than a single note – that affect its resonant properties after the end of the conventional manufacturing process, e.g. mutes and other preparations [16]. The only example of node in the MedleyDB taxonomy reaching this level is *tack piano* [9].

Unlike musical instruments, which are approximately amenable to a hierarchical taxonomy of resonating objects, IPTs result from a complex synchronization between multiple gestures, which may involve both hands and arms, as well as diaphragm, vocal tract, and sometimes the whole body. As a result, there is no immediate way to interface them with H-S, or indeed any tree-like structure [28]. Instead, every playing technique is described by a finite collection of categories, each belonging to a different “namespace”; Figure 3 illustrates such namespaces in the case of the violin. It therefore appears that, rather than aiming for a mere increase in granularity with respect to H-S, a coherent research program around extended playing techniques should formulate them as belonging to a meron-
 311 312 313 314 315 316 317 318 319 320 321 322 323 324 325 326 327 328 329 330 331 332 333 334 335 336 337 338 339 340 341 342 343 344 345 346 347

3.2 Application setting and evaluation

In what follows, we adopt a middle ground position between the two aforementioned approaches: neither a supervised classifier (as in a hierarchical taxonomy), nor a caption generator (as in a meron-
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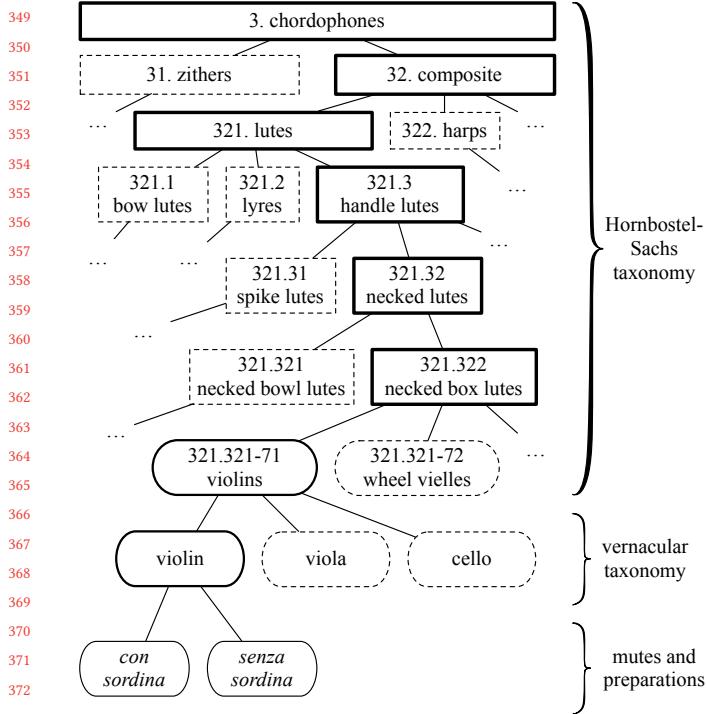


Figure 2: Taxonomy of musical instruments.

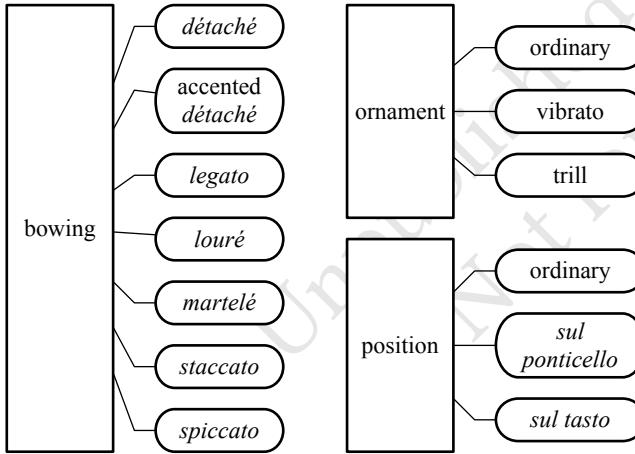


Figure 3: Namespaces of violin playing techniques.

any user-defined audio query $\mathbf{x}(t)$. In the context of contemporary music creation, this $\mathbf{x}(t)$ may be an instrumental or vocal sketch; a sound event recorded from the environment; a computer-generated waveform; or any mixture of the above [39]. Upon inspecting the k nearest neighbors returned by the search engine, the composer may decide to retain one of the retrieved notes, in which case its attributes (pitch and intensity, but also the exact playing technique) are readily available and can be included into the musical score to approximate the query.

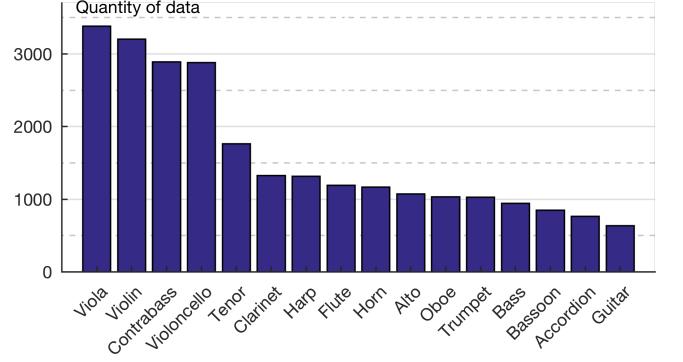


Figure 4: Instruments in the SOL dataset.

Faithfully evaluating such a system is a difficult procedure, and ultimately would rest on its practical usability, as judged by the composers themselves. Nevertheless, a useful quantitative metric for this task is the precision at k ($P@k$) of the test set with respect to the training set, both under a instrument taxonomy and an IPT taxonomy. In all subsequent experiments, we report $P@k$ after setting the number of retrieved items to $k = 5$.

3.3 Studio On Line dataset (SOL)

The Studio On Line dataset (SOL) was recorded at Ircam in 2002 and is freely downloadable as part of the Orchids software for computer-assisted orchestration.¹ It comprises 16 musical instruments playing 25444 isolated notes in total. The distribution of these notes, shown in Figure 4, spans the full combinatorial diversity of applicable intensities, pitches, preparations (i.e. mutes), as well as all applicable playing techniques. The distribution of playing techniques – whose most common are shown in Figure 5 – is heavy-tailed (average 178, standard deviation 429): this is because some playing techniques are shared between many instruments (e.g. *tremolo*) whereas other are instrument-specific (e.g. *xylophonic* which is specific to the harp). The SOL dataset has 143 IPTs in total, and 469 applicable instrument-mute-technique triplets.

4 METHODS

In this section, we describe the scattering transform and supervised metric learning used to implement all query-by-example systems in our benchmark.

4.1 Scattering transform

The scattering transform is a cascade of two wavelet modulus operators, each followed by temporal averaging: the first layer extracts the average spectral envelope $S_1\mathbf{x}(\lambda_1)$ of $\mathbf{x}(t)$ at frequencies λ_1 , whereas the second layer $S_2\mathbf{x}(\lambda_1, \lambda_2)$ extracts amplitude modulations of this spectral envelope at rates λ_2 . The set of frequencies discretizes the auditory range according to the mel scale, with $Q_1 = 12$ bins per octave at topmost frequencies; whereas rates λ_2 follow a geometric sequence between λ_1 and some minimal rate T^{-1} , with $Q_2 = 1$ bin per octave. We refer to [2] for a general introduction to scattering transforms in audio classification, and to [33,

¹Link to SOL dataset: <http://forumnet.ircam.fr/product/orchids-en/>

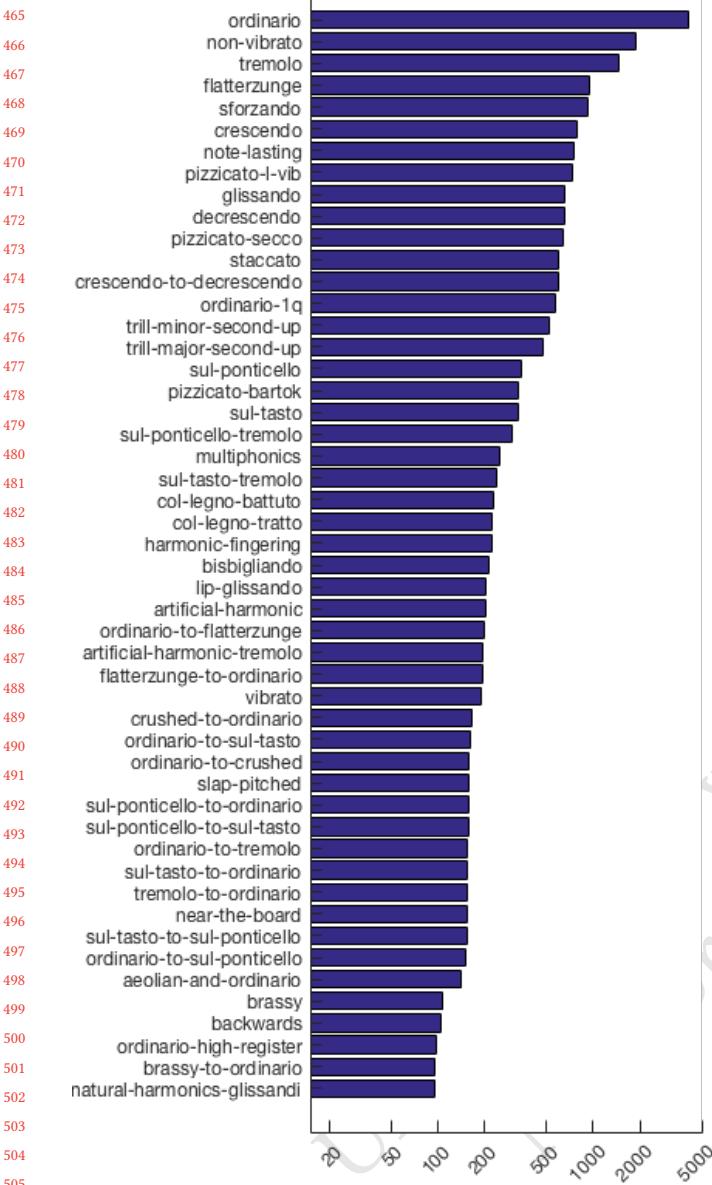


Figure 5: Playing techniques in the SOL dataset.

sections 3.2 and 4.5] for a discussion on its application to musical instrument classification in solo recordings, as well as its close connections with STRF. The scattering transform is theoretically suited to model extended playing techniques, since various values of the rate λ_2 characterize some of the most common nonstationarities in sound production, including tremolo, vibrato, and dissonance [1, section 4]. In the following, we denote by $\mathbf{Sx}(\lambda)$ the concatenation of all scattering coefficients, whether the generic scattering path λ corresponds to a singleton (λ_1) or a pair (λ_1, λ_2).

In order to match a decibel-like perception of loudness, we apply the path-adaptive, quasi-logarithmic compression

$$\tilde{\mathbf{Sx}}_i(\lambda) = \log \left(1 + \frac{\mathbf{Sx}_i(\lambda)}{\varepsilon \times \mu(\lambda)} \right) \quad (1)$$

where $\varepsilon = 10^{-3}$ and $\mu(\lambda)$ is the median value of the scattering coefficient $\mathbf{Sx}_i(\lambda)$ for path λ across samples i .

4.2 Metric learning

Linear metric learning algorithms generate a matrix \mathbf{L} such that the Mahalanobis distance

$$\mathbf{D}_{\mathbf{L}}(\mathbf{x}_i, \mathbf{x}_j) = \|\mathbf{L}(\tilde{\mathbf{Sx}}_i - \tilde{\mathbf{Sx}}_j)\|_2 \quad (2)$$

between all pairs of samples $(\mathbf{x}_i, \mathbf{x}_j)$ optimizes some objective function. We refer to [4] for a review of the state of the art. In particular, the large-margin nearest neighbors (LMNN) algorithm aims at bringing all k nearest neighbors \mathbf{x}_j of every \mathbf{x}_i closer than the canonical Euclidean distance $\mathbf{D}(\mathbf{x}_i, \mathbf{x}_j) = \|\tilde{\mathbf{Sx}}_i - \tilde{\mathbf{Sx}}_j\|_2$ if \mathbf{x}_i and \mathbf{x}_j belong to the same class, and further apart otherwise. The matrix \mathbf{L} is obtained by applying the special-purpose solver of [53, appendix A]. In subsequent experiments, disabling LMNN is equivalent to setting \mathbf{L} to the identity matrix, and retrieving a list of k nearest neighbors from $\mathbf{x}_i(t)$ according to the canonical Euclidean distance in feature space rather than the Mahalanobis distance.

As compared to a class-wise generative model (such as Gaussian mixtures), a global linear model ensures some robustness to minor alterations of the taxonomy, which is important in the context of IPT: e.g. what some instrumentists may call *slide*, others will call *glissando*. Furthermore, although one of its major drawback relies on its strong dependency on the Euclidean neighbors to determine intra-class variability [43], this drawback is alleviated in the case of a feature space based on scattering transform coefficients, whose Euclidean metric provably approximates the extent of elastic deformation needed to shear $\mathbf{x}_i(t)$ into $\mathbf{x}_j(t)$ in the time-frequency domain [38, Theorem 2.16].

5 EXPERIMENTAL RESULTS

In this section, we apply the aforementioned methods to instrument and IPT query-by-example retrieval in the Studio On Line (SOL) dataset.

5.1 Evaluation of instrument recognition

In the task of instrument recognition, each of the k elements \mathbf{x}_j returned by the system is considered relevant to the query \mathbf{x}_i if and only if \mathbf{x}_i and \mathbf{x}_j correspond to the same instrument, regardless of pitch, intensity, and playing technique.

We compare scattering features to a baseline of mel-frequency cepstral coefficients (MFCC), corresponding to the 13 lowest frequencies after applying a discrete cosine transform (DCT) on the logarithm of the 40-band mel-frequency spectrum. In addition, we vary the maximum time scale T of amplitude modulation between 25 ms and 1 s. In the case of MFCC, $T = 25$ ms corresponds to the inverse of the lowest audible frequency ($T^{-1} = 40$ Hz). Therefore, increasing the frame duration T has no effect on the value of MFCC, because the mel-spectrogram is equivalent to a local averaging of the wavelet scalogram at the time scale T , leaving unchanged the

581 global averaging of $Sx(\lambda)$ at the time scale of whole musical notes
 582 [1, section II.B].

583 Figure 6 (left) summarizes our results. We find that MFCC reach
 584 a relatively high P@5 of 89%. Keeping all 40 quefrequencies rather than
 585 the lowest 13 brings the P@5 down to 84%, because the highest
 586 quefrequencies are the most affected by some spurious factors of intra-
 587 class variability, namely pitch and spectral flatness [33, subsection
 588 2.3.3].

589 At the smallest time scale $T = 25$ ms, the scattering transform
 590 reaches a P@5 of 89%, thus matching exactly the performance of
 591 MFCC. This is because the relatively few second-order scattering
 592 coefficients whose rate λ_2 exceeds 40 Hz have a negligible effect on
 593 Euclidean distances, as they carry very little energy [2]. Moreover,
 594 disabling median renormalization – i.e. setting $\mu(\lambda) = 1$ for all
 595 scattering paths λ – degrades P@5 down to 84%, while disabling
 596 logarithmic compression altogether – i.e. the limit case $\varepsilon \rightarrow \infty$ –
 597 degrades it to 76%. These results are consistent with another
 598 publication [?], which applies scattering transform to a query-by-
 599 example retrieval task among environmental acoustic scenes.

600 On one hand, replacing the canonical Euclidean distance by a
 601 Mahalanobis distance learned by the LMNN algorithm marginally
 602 improve P@5 in the case of the MFCC baseline, from 89.3% to 90.0%.
 603 On the other hand, applying LMNN on scattering features strongly
 604 enhances their performance with respect to the Euclidean distance,
 605 from 89.1% to 98.0%.

606 The gain in precision afforded by scattering coefficients over
 607 MFCC could simply be caused by a higher number of dimensions.
 608 To refute this hypothesis, we supplement the 13 coefficients resulting
 609 from a global averaging at the time scale of full musical notes
 610 by higher-order summary statistics, namely polynomial features of
 611 degrees 2 and 3. Instrument retrieval in the resulting feature space,
 612 whose dimension (494) is comparable to the number of scattering
 613 coefficients, has a P@5 of 91%, i.e. slightly above the baseline. There-
 614 fore, it is more likely the multiresolution structure of scattering
 615 coefficients, rather than its dimensionality, that causes a strong
 616 boost in performance.

617 Lastly, increasing T from 25 ms up to 1 s – that is, including all
 618 amplitude modulations between 1 Hz and 40 Hz – brings LMNN to
 619 a near-perfect P@5 of 99.71%. Not only does this result confirm
 620 that well-established methods in audio signal processing (here,
 621 wavelet scattering and metric learning) are sufficient to retrieve the
 622 instrument from a single ordinary note; it also demonstrates that the
 623 results remain excellent despite large intra-class variability within
 624 instruments: in pitch and intensity, but also in the usage of mutes
 625 and extended IPTs. In other words, the monophonic recognition
 626 of Western instruments is, all things considered, a solved problem
 627 indeed.

628 5.2 Evaluation of playing technique 629 recognition

630 The situation is different when considering IPT, rather than instrument,
 631 as reference for evaluating the reference of the query-by-
 632 example search engine. The MFCC baseline has a relatively low
 633 P@5 of 44.5%, which indicates that a coarse description of the short-
 634 term spectral envelope is rarely ever sufficient to model acoustic
 635 similarity in IPT. Perhaps more surprisingly, we find that only the

636 system combining all presented improvements, i.e. log-scattering
 637 coefficients with median renormalization, $T = 500$ ms, and LMNN,
 638 strongly outperforms the MFCC baseline, with a state-of-the-art
 639 P@5 of 63.0%. Indeed, an ablation study of that system reveals that,
 640 all other things being equal: reducing T to 25 ms brings the P@5 to
 641 53.3%; disabling LMNN, 50.0%; and replacing scattering coefficients
 642 by MFCC, to 48.4%.

643 What stems from these observations is that, unlike instrument
 644 similarity, IPT similarity results from long-range temporal depen-
 645 dencies in the audio signal. In addition, the dissimilarity between
 646 two different playing techniques is not a matter of elastic deforma-
 647 tion in the time-frequency domain – as approximated by Euclidean
 648 distance in the feature space of scattering coefficients – but also in-
 649 volves an adaptive process which combines the saliences of various
 650 acoustic frequencies and modulation rates in several nonuniform
 651 ways, thus producing a metric that favors certain factors of acoustic
 652 variability while mitigating others.

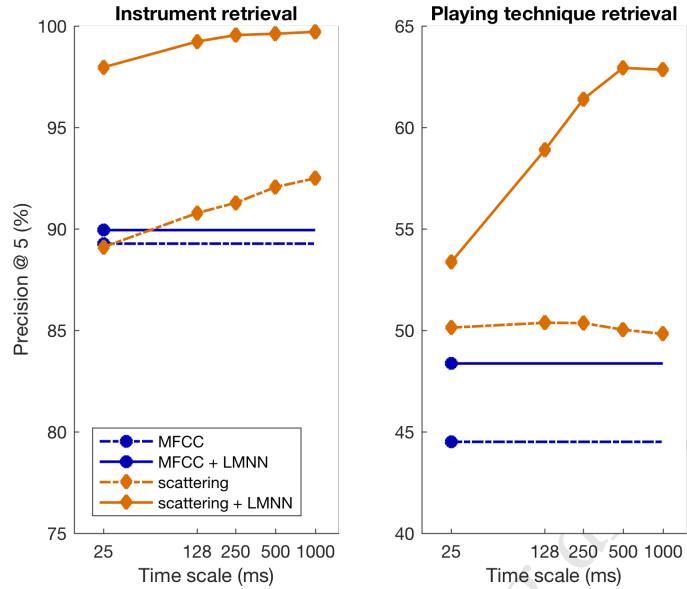
653 6 CONCLUSION

654 Whereas the MIR literature abounds on the topic of musical instru-
 655 ment recognition in so-called “ordinary” isolated notes and solo
 656 performances, little is known about the problem of retrieving the
 657 instrumental playing technique (IPT) of an audio query within a
 658 fine-grained taxonomy. Yet, the knowledge of IPT is a precious
 659 source of music information, not only to characterize the physical
 660 interaction between player and instrument, but also in the realm
 661 of contemporary music creation. In all likelihood, it also bears an
 662 interest for organizing digital libraries, as a mid-level descriptor of
 663 musical style. To the best of our knowledge, this paper is the first
 664 in benchmarking query-by-example MIR systems according to a
 665 large-vocabulary IPT reference (143 classes) instead of an instru-
 666 ment reference. We find that this new task is considerably more
 667 challenging than musical instrument recognition, as it amounts to
 668 characterizing spectrotemporal patterns at various scales and rates
 669 and comparing them in a highly non-Euclidean way. Although the
 670 combination of methods presented here – wavelet scattering and
 671 large-margin nearest neighbors – outperforms the MFCC baseline
 672 (even at comparable dimensionalities and number of learnable pa-
 673 rameters), its accuracy on the SOL dataset certainly leaves some
 674 room for future improvements.

675 The evaluation methodology presented here uses ground truth
 676 IPT labels to quantify the relevance of returned items. Despite
 677 the advantage of unequivocality, it might be too harsh to reflect
 678 practical use. Indeed, as it is often the case in MIR, some pairs
 679 of labels are subjectively more similar than others: e.g. *slide* is
 680 evidently closer to *glissando* than to *pizzicato-bartok*. The collection
 681 of subjective ratings of IPT similarity, and its comparison with
 682 automated ratings, is left as future work.

683 ACKNOWLEDGMENTS

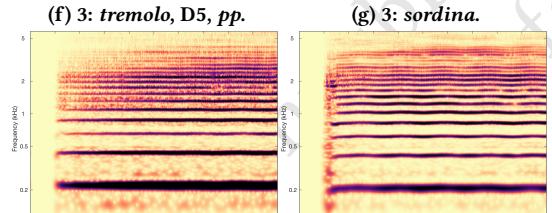
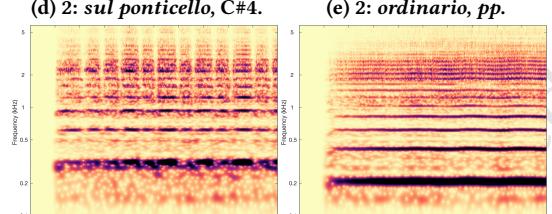
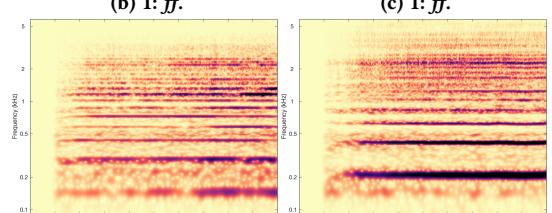
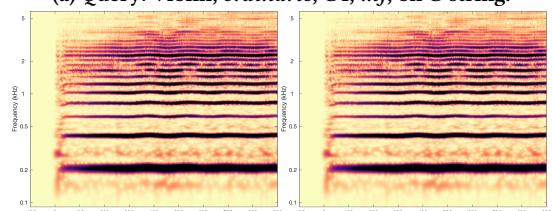
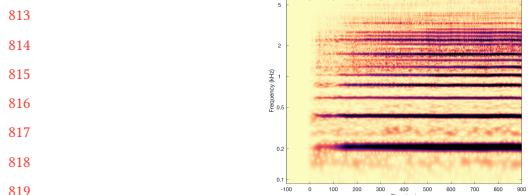
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 689 Visipedia; and Katherine Crocker for helpful suggestions on the title

**Figure 6: Summary of results on the SOL dataset.**

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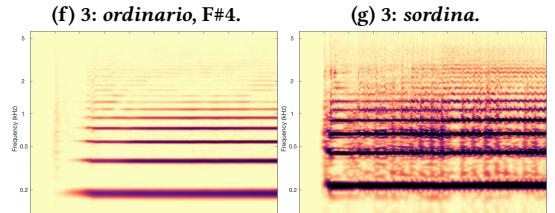
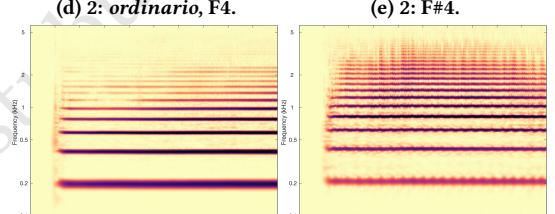
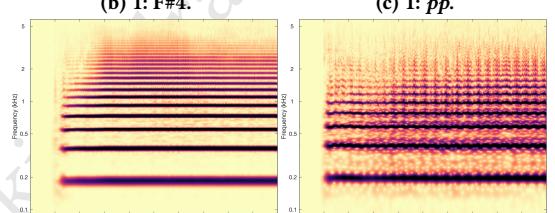
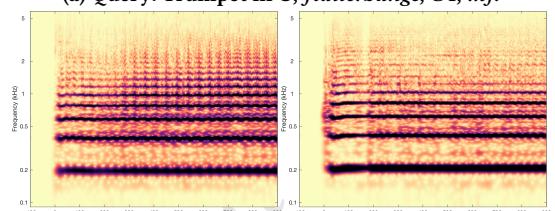
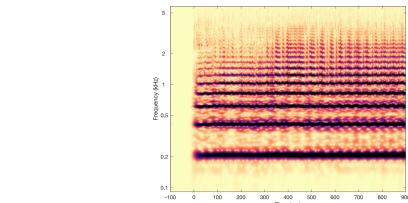
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(j) 5: *tremolo*, C#5, *pp*. (k) 5: on D string.

Figure 7: .



(j) 5: *ordinario*. (k) 5: F4, *pp*.

Figure 8: .

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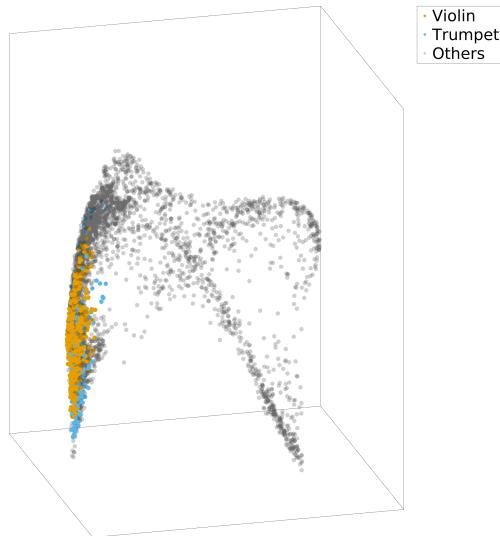
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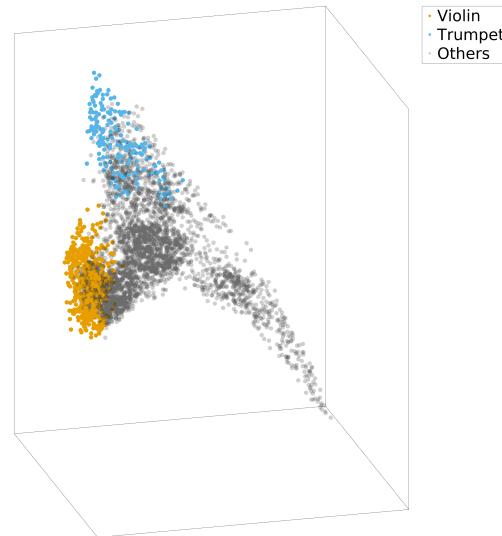
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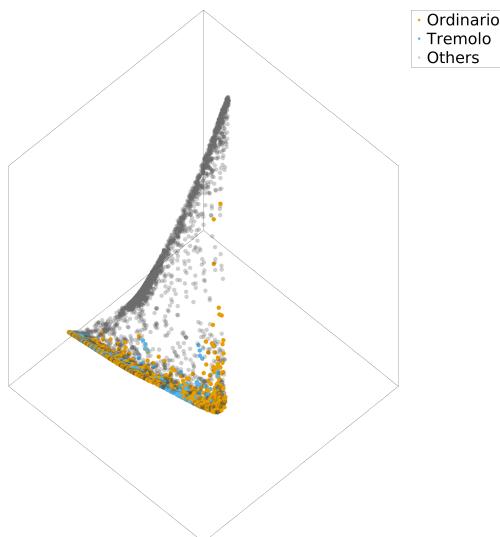
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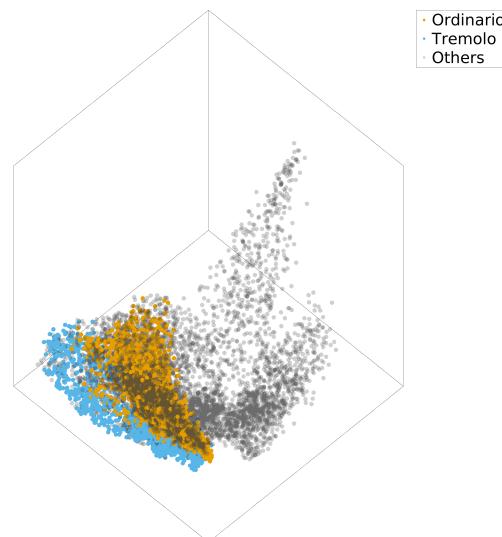
(a) .



(b) .



(c) .



(d) .

Figure 9: .

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