

Learned Features for the Assessment of Percussive Music Performances

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Abstract—The automatic assessment of (student) music performance involves the characterization of the audio recordings and the modeling of human judgments. To build a computational model that provides a reliable assessment, the system must take into account various aspects of a performance including technical correctness and aesthetic standards. While some progress has been made in recent years, the search for an effective feature representation remains open-ended. In this study, we explore the possibility of using learned features from sparse coding. Specifically, we investigate three sets of features, namely a baseline set, a set of designed features, and a feature set learned with sparse coding. In addition, we compare the impact of two different input representations on the effectiveness of the learned features. The evaluation is performed on a dataset of annotated recordings of students playing snare exercises. The results imply the general viability of feature learning in the context of automatic assessment of music performances.

I. INTRODUCTION

Music performance is a sequence of actions that integrates both cognitive and motor skills. Starting from the musical ideas, this process of converting thoughts into movements is, as pointed out by Palmer [1], among the most skill-intensive actions produced by human beings. To cultivate these skills, the qualitative assessment by peers and teachers is an essential pedagogical component in music education. A systematic assessment that is able to facilitate improvements usually requires careful examination of different aspects of a performance, such as technical correctness and alignment with aesthetic ideals. This task, however, is extremely difficult due to its subjective nature. As a result, human raters tend to exhibit a large variance in terms of their severity, rating scale, and the interpretation of rating categories [2]; the bias of the raters and the ill-defined categories, as suggested by Thompson and Williamon [3], could adversely impact both the discriminability and the fairness of assessment. A computational approach that provides consistent and repeatable feedback, as illustrated in Fig. 1, might offer a potential solution to this issue and enhance the students' learning experience.

With recent advances in the field of Music Information Retrieval (MIR) for tasks such as music transcription [4] and source separation [5], the realization of intelligent music systems with reliable functionality became plausible, opening up new possibilities for music education [6]. Commercial soft-

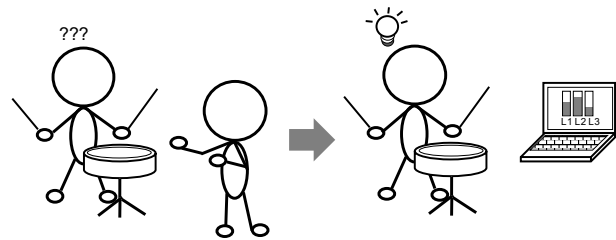


Fig. 1. The concept of automatic music performance assessment systems.

ware such as SmartMusic¹ and Yousician² both showcase how automatic assessment tools could enhance the music learning process with more flexible practice sessions and individualized feedback. These efforts, while providing rudimentary solutions to the users, still fall short in characterizing non-technical aspects of a performance. We hypothesize that this limitation originates from the design of the audio features. In MIR, a set of well-established features has proven to be surprisingly successful in applications such as music genre classification [7], music emotion recognition [8], and drum sound classification [9], however, using the same features for other tasks such as music performance assessment has been shown lead to sub-optimal performance [10], [11].

In this paper, we explore the possibility of applying unsupervised feature learning in the context of music performance assessment. In particular, we compare the effectiveness of a set of baseline features, designed features, and learned features in assessing students' snare drum performances from a large set of recordings of the Florida all-state auditions. A successful set of features would clearly describe the acoustic events rendered by the performers, providing a good foundation for studying the connection between music performance and its corresponding assessment given by the human judges. Therefore, the goal of this paper is to find optimal features for characterizing percussive instrument performances.

The contributions of this paper include:

- (i) new insights into the viability of applying feature learning to the problem of automatic music performance assessment,

¹<http://www.smartmusic.com> Last access: 2017/10/15

²<http://yousician.com> Last access: 2017/10/15

- (ii) a new input representation that characterizes percussive instrument performances for feature learning purposes, and
- (iii) the demonstration of potential improvements in predicting judges' ratings using the proposed method.

The remainder of this paper is structured as follows: Section II presents the related work in automatic music performance assessment and feature learning. In Sect. III, we introduce our proposed method. The experiment setup and results are described in Sect. IV. Finally, the conclusion and future directions are presented in Sect. V.

II. RELATED WORK

Music Performance Analysis (MPA) is a research field that concerns the study of the acoustic rendition of a musical score or idea [12]. Instead of analyzing the intentions of the composer from the symbolic representation of a music composition, MPA focuses on interpreting the artistic decisions made by the performers during their music performance. For example, the same score can be played in different tempi or with different dynamics, resulting in performances with various levels of expressiveness. One of the main challenges of MPA, therefore, is to associate these expressions with human perception in a musically meaningful way.

To automate the process of MPA, a system must handle the extraction and interpretation of the important parameters of music performances. In the early research, most of the analysis was performed on symbolic data extracted from external sensors or MIDI devices. Recently, the focus has gradually shifted to the analysis of audio recordings. The basic approach to this problem usually involves the careful design of audio features that are capable of extracting the most relevant information in different contexts. For instance, Nakano presented an automatic system that evaluates the singing skill of the users [13]; by characterizing the performances through pitch interval accuracy and vibrato features, the system was able to classify the performance into the two classes *good* and *poor*. Abeßer et al. propose a system that automatically assesses the quality of vocal and instrumental performances of 9th and 10th graders [14]. Features representing the pitch, intonation, and rhythmic correctness are designed to quantify the students' performances. They report that the system is able to predict four different performance qualities with occasional confusions between the adjacent classes. In a system that identifies the common mistakes by the flute beginners, Han and Lee propose to use features such as MFCCs with sparse filtering for detecting events such as poor blowing and misfingering [15]. More recently, Wu et al. and Vidwans et al. propose to assess students' instrumental performances using a set of features derived from pitch, amplitude, and inter-onset interval histograms [10], [11]. The evaluation results show reasonable correlation between the model predictions and expert judges' ratings.

All of the above mentioned systems use custom-designed features in the analysis pipeline. This approach, while translating existing music domain knowledge into machine operations,

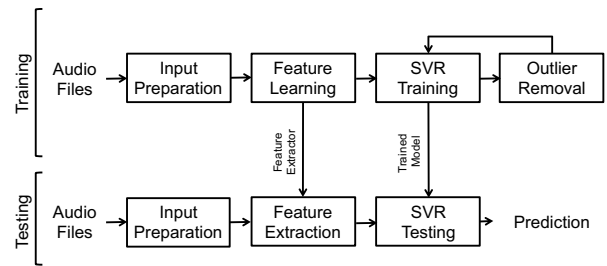


Fig. 2. The flowchart of the proposed method.

might also strip away important information that resides in the data. Feature learning, on the other hand, allows an algorithm to find the most fitting features based on given input representations. Several feature learning methods have been found successful in music related applications, especially for the task of music genre recognition. For example, Lee et al. applied convolutional Deep Belief Networks (DBNs) to magnitude spectrograms to learn features [16]; the evaluation results show that the learned features outperform conventional audio features in recognizing music genre. Similarly, Hamel and Eck demonstrate that a DBN is able to derive features that achieve state-of-the-art performance in music genre recognition [17]. Henaff et al. apply Sparse Coding (SC) to the log spectrogram and use the learned features to train a SVM classifier. The evaluation results also indicate the effectiveness of the learned features for recognizing music genres [18]. Nam et al. further introduce a pre-processing pipeline that improves the SC feature learning [19]; the evaluation results on a music tagging dataset compare favorably against the commonly used audio features. More recently, SC-derived features have also been shown effective for music genre recognition [20] and music emotion recognition [21].

Based on the findings in the previous work, both DBNs and SC seem to be useful approaches for feature learning in music related tasks. Compared with DBNs, however, SC seems to have a broader range of applications in addition to the MGR task. Therefore, in this study, we propose to explore the viability of applying sparse coding for music performance assessment.

III. METHOD

A. System Overview

The proposed system comprises both a training and a testing phase. As shown in Fig. 2, the training phase starts by transforming each audio recording into the input representation; the input representations are collected for the training data and passed to the feature learning block. In the feature learning step, the feature extractor is derived by solving an optimization problem across the entire dataset, and the corresponding feature vector for each recording is calculated. Finally, the features are used to train a regression model that minimizes the loss between the model prediction and the ground truth (judges' ratings) for each recording, along with an outlier removal step to refine the model.

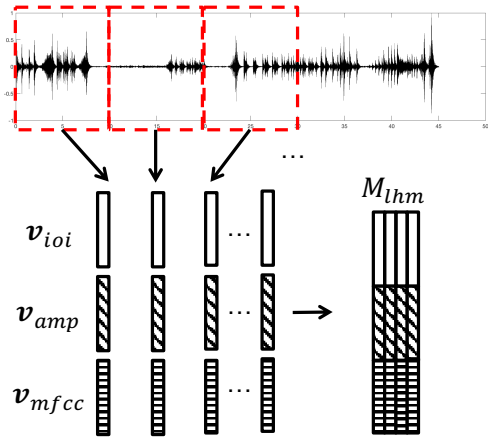


Fig. 3. Illustration of the construction process of local histogram matrix; \mathbf{v}_{ioi} is the IOI histogram vector, \mathbf{v}_{amp} is the amplitude histogram vector, \mathbf{v}_{mfcc} is the averaged MFCCs vector, and M_{lhm} is the local histogram matrix.

In the testing phase, a similar procedure is followed for each recording to prepare the input representation and extract features using the derived feature extractor. The resulting feature vector is then used to predict the judges' ratings with the pre-trained regression model. In the following sections, more details of each processing step are presented.

B. Input Preparation

The goal of the input preparation step is to normalize, reduce the amount of data, and to convert the data into meaningful input representations. First, audio recordings are down-mixed to mono and resampled to a sampling rate of 22.05 kHz after decoding. All files are normalized to a numerical range between -1 and 1. Finally, two different matrix representations are computed, namely the Short-Time Fourier Transform (STFT) and a Local Histogram Matrix (LHM).

1) *STFT*: The STFT is computed using a block size of 512 samples with 75% overlapping blocks; a Hann window is applied to each block. Only the magnitude spectrogram is used and the phase information is discarded. The resulting spectrogram M_{stft} is a $m \times n$ matrix, in which $m = 257$ and n equals the number of blocks. This input representation has been referred in some related literatures as a baseline [22], [23].

2) *LHM*: This input representation aims to capture the most important overall characteristics of the percussive instrument performances. The extraction process of the local histogram matrix is shown in Fig. 3. In order to extract the histogram, the input time-domain audio signal is first partitioned into non-overlapping local segments of length 10 s. This length enables us to capture higher level structure such as music phrases. Within each segment, the Inter-Onset-Interval (IOI) histogram vector \mathbf{v}_{ioi} , the amplitude histogram vector \mathbf{v}_{amp} , and the averaged MFCC vector \mathbf{v}_{mfcc} is extracted. Concatenating these vectors will result in local histogram matrix M_{lhm} that represents each individual recording. The definitions of these vectors are:

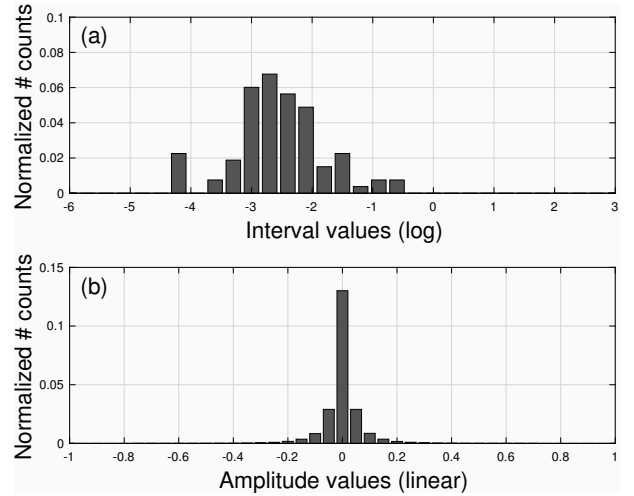


Fig. 4. An example of (a) an IOI histogram vector \mathbf{v}_{ioi} and (b) an amplitude histogram vector \mathbf{v}_{amp} . All histograms are normalized by the total number of counts and can be interpreted as probability distributions.[ok](#)

- (i) **IOI histogram vector (\mathbf{v}_{ioi})**: the onset times, i.e., the start times of individual drum events are estimated within the local segment using a standard spectral flux novelty function and an adaptive median threshold for peak picking; the implementation follows the description in [24] and results in a vector $onset(i)$ in which i is the onset index. The IOI sequence is calculated by $IOI = diff(onset(i))$, followed by a non-linear transformation $IOI_{ln} = \ln(IOI)$. Since the ratios between onset intervals are frequently powers of 2 (e.g., an 8th note is twice as long as a 16th note), this transformation helps to characterize the rhythmic patterns within a musically more meaningful numerical range. Next, the \mathbf{v}_{ioi} is computed by estimating the histogram from the IOI_{ln} with a pre-defined range and resolution, determined through data observation in pilot experiments. Finally, the \mathbf{v}_{ioi} is normalized by dividing the total number of onsets in the entire recording. The resulting \mathbf{v}_{ioi} is a column vector with dimensionality $d_{ioi} = 31$. An example of \mathbf{v}_{ioi} is shown in Fig. 4(a).
- (ii) **Amplitude histogram vector (\mathbf{v}_{amp})**: following a procedure similar to the one described above, \mathbf{v}_{amp} is calculated by estimating the histogram of the amplitude values within the local segment. The range of the histogram is from -1 to 1 with a resolution of 0.05 between the consecutive bins. The \mathbf{v}_{amp} is normalized by the total number of samples in the entire recording. This is represented as a column vector of dimensionality $d_{amp} = 41$. An example of \mathbf{v}_{amp} is shown in Fig. 4(b).
- (iii) **Averaged MFCC vector (\mathbf{v}_{mfcc})**: given a local segment, the first 13 Mel Frequency Cepstral Coefficients (MFCCs) are computed using the same block size and overlap as defined in Sect. III-B1, which leads to a $13 \times n_b$ matrix where n_b is the number of blocks within the segment. Next, the \mathbf{v}_{mfcc} is calculated by averaging the MFCC

matrix across the n_b blocks, resulting in a column vector of dimensionality $d_{mfcc} = 13$.

The same procedure will repeat for each 10-second local segment, resulting in the final matrix M_{lhm} is a $m' \times n_s$ matrix, in which

$$m' = d_{ioi} + d_{amp} + d_{mfcc} = 85 \quad (1)$$

and n_s is the number of local segments.

C. Feature Learning

The feature learning algorithm used in this paper is Sparse Coding (SC), which can be expressed as

$$\hat{\alpha} = \underset{\alpha}{\operatorname{argmin}} \frac{1}{2} \|X - D\alpha\|_2^2 + \lambda \|\alpha\|_1, \quad (2)$$

with $X \in R^{m \times n}$ as the input matrix, i.e., M_{stft} or M_{lhm} . D is the $m \times k$ dictionary matrix, α is the $k \times n$ sparse matrix, λ is the sparsity coefficient, n is the number of local segments, and k is the user-defined dictionary size.

This ℓ_1 regularized Least Absolute Shrinkage and Selection Operator (LASSO) problem can be solved by the Least Angle Regression (LARS) algorithm efficiently [25], in which the dictionary D and the sparse matrix α can be learned by iteratively minimizing the reconstruction loss. Finally, the resulting dictionary D can be considered as the feature extractor, where the corresponding sparse representation α can be used to compute the features.

To compute the final feature vector that represents each audio recording, our system first learns an universal dictionary D_{all} from the entire dataset. This can be done by concatenating the M_{stft} or M_{lhm} across all the training files, and solve the LASSO optimization problem on the concatenated matrix X_{all} . Next, the $\alpha_{individual}$ is estimated from each recording by substituting the X in Eq. 2 with the input representation of an individual file $X_{individual}$ while keeping the $D = D_{all}$ fixed throughout the optimization process. The resulting $\alpha_{individual}$ is a $k \times n$ sparse matrix. Finally, $\alpha_{individual}$ is aggregated using mean and standard deviation across n segments, producing a feature vector $\alpha_{final} = [mean(\alpha_{individual}); std(\alpha_{individual})]$ with a dimensionality of $d_{final} = 2 \times k$. $[\cdot]$ is a vector concatenation operator.

In our experiment, the Matlab implementation for SC from the open source library SPAMS³ [26] is used. For parametrization, $k = \{32, 64, 128\}$ has been tested, and the sparsity coefficient $\lambda = 1/\sqrt{block\ size}$ is applied.

D. Regression Model

The regression model used is Support Vector Regression (SVR) with a linear kernel. The Matlab implementation of this algorithm from the open source library libsvm [27], is used with default settings. Due to the limited size of sample pool (see Sect. IV-A for more details), a Leave One Out (LOO) cross-validation scheme is applied to our evaluation process. The main idea of LOO is to sequentially select one sample from the pool as test data and use the rest of the pool as training

TABLE I
STATICS OF THE MIDDLE SCHOOL SNARE ETUDE FROM 2013 TO 2015

Middle school/ Percussion/ Snare Etude			
Year	#Students	Total Dur (sec)	Average Dur (sec)
2013	98	4953	50
2014	90	4595	51
2015	86	4608	53

data until all the samples have been tested. Additionally, an outlier removal process is implemented by iteratively removing the sample with the largest residual between the prediction and the actual label until 5% of the entire data is eliminated. This process potentially helps the regressor to better capture the underlying patterns of the data.

IV. EXPERIMENTS

A. Dataset

The dataset used for this study is provided by the Florida Bandmasters Association (FBA). This dataset contains audio recordings from the Florida all-state auditions of three groups of students: middle school (7th and 8th graders), concert band (9th and 10th graders), and symphonic band (11th and 12th graders) for three consecutive years (2013 to 2015). A total number of 19 types of instruments are included in the auditions. As a result, this dataset can be split into different subsets of recordings by their year, group, and instrument (e.g., 2013, middle school, clarinet). Each subset contains up to 180 recordings of student performances.

In each recording, a student is required to perform several exercises, such as technical etude, lyrical etude, chromatic scale, 12 major scales, and sight-reading. Each exercise is graded by expert judges using assessment categories such as *musicality*, *note accuracy*, *rhythmic accuracy*, *tone quality*, *artistry*, and *articulation*. The number of judges and the grading criteria are not available. The maximum score of these categories vary from 5 to 40. In our experiments, all of the ratings are normalized to a range between 0 and 1 by dividing the score with the maximum allowed value of the corresponding category. More information on the dataset can be found in our Github repository.⁴

In this study, the focus is on assessing percussion performance. For percussion instruments, the audition session includes 5 different exercises, which are mallet etude, snare etude, chromatic scale (xylophone), 12 major scales (xylophone), and sight-reading (snare). To further narrow down the scope of this study, we use only the subset of middle school snare etude from all three years. This particular combination is selected for containing a comparably high number of students. As shown in Table I, a total number of 274 recordings of snare etude with an averaged duration of 51.3 s is available for analysis. For this particular exercise, the assessment categories are musicality (L1) and rhythmic accuracy (L2).

³<http://spams-devel.gforge.inria.fr> Last accessed: 2017/10/15

⁴<https://github.com/GTCMT/FBA2013>, Last access: 2017/10/15

B. Experiment Setup

This paper presents two experiments that highlight different characteristics of the proposed feature learning method in the context of assessing student snare drum performances. The goal of Experiment 1 is to compare the effectiveness of two different input representations (see Sect. III-B) for SC. For Experiment 2, the goal is to find the best combination of feature sets in order to achieve the highest performance.

In Experiment 1, the tested configurations are:

- (i) **SC (STFT)**: sparse coding features using STFT as input representations and
- (ii) **SC (LHM)**: sparse coding features using LHM as input representations.

Both configurations are tested using $k = \{32, 64, 128\}$.

In Experiment 2, the regression model trained on the SC learned features using the proposed LHM with $k = 32$ is compared to two different sets of features, referred to as *Baseline* and *Designed* features, as proposed by Wu et al. [10]. The regression performance of the following feature set combinations is tested:

- (i) **Baseline**: the standard spectral and temporal features such as spectral centroid, spectral rolloff, spectral flux, zero-crossing rate, and 13 MFCCs. The dimensionality is $d_{\text{baseline}} = 68$.
- (ii) **Designed**: the designed rhythmic and dynamic features derived from the IOI and amplitude histograms. These features involve the calculation of various statistics, such as crest, skewness, flatness, kurtosis, etc., directly from the histograms of the entire recording (compare [10] for more details). The dimensionality is $d_{\text{designed}} = 18$.
- (iii) **SC (LHM)**: see Sect. III-C.
- (iv) **Designed + Baseline**: a combined feature set consisting of both baseline and designed features.
- (v) **SC + Baseline**: a combined feature set consisting of both SC and baseline features.
- (vi) **SC + Designed**: a combined feature set consisting of both SC and designed features.

C. Metrics

The performance of the models is investigated using the following standard statistical metrics: the Pearson correlation coefficient r and the coefficient of determination, i.e., R^2 . These metrics are commonly used to evaluate the strength of the relationship between the regression predictions and ground truth. Details of the mathematical formulations can be found in [28].

D. Experiment Results

In this section, the evaluation results of both experiments are presented and discussed. Since all of the correlation results are significant ($p \ll 0.05$), their p-values are not reported.

The evaluation results of Experiment 1 are shown in Table II. The following trends can be observed: first, the LHM input representation outperforms the STFT representation in almost

TABLE II
EVALUATION RESULTS FOR EXPERIMENT 1: L1 REPRESENTS MUSICALITY, AND L2 REPRESENTS RHYTHMIC ACCURACY. THE HIGHER IS BETTER.

Input Representation		STFT		LHM	
Dictionary Size	Metrics	L1	L2	L1	L2
k = 32	r	0.34	0.19	0.65	0.57
	R^2	0.08	-0.02	0.41	0.29
k = 64	r	0.41	0.26	0.70	0.50
	R^2	0.11	-0.00	0.45	0.06
k = 128	r	0.41	0.28	0.33	0.34
	R^2	0.08	-0.07	-0.08	-0.78

every case. This result clearly shows that for this task, LHM is a more effective input representation than STFT. A likely explanation is that this discrepancy originates from the representations' capabilities of capturing temporal information. Since the STFT only represents the spectral content at various single instances, it does not encapsulate any temporal dependencies between meaningful audio events such as consecutive drums hits. This temporal information, while being likely to reside in the sparse matrix α , will be lost after the feature aggregation. The absence of temporal information apparently poses a problem for SC to learn higher level music concepts such as rhythm. LHM, on the other hand, captures some temporal dependencies between the audio events with the IOI histograms. This allows for the rhythmic information to be translated into the SC dictionary and to reflect on the final features, leading towards a better performance. Second, both STFT and LHM perform poorly for the largest dictionary size with $k = 128$. The reason behind this degradation for both representations might be due to the limited size of the sample pool. When $k = 128$, the resulting feature dimensionality, as described in Sect. III-C, would be $k \times 2 = 256$. This will result in a feature matrix of 274×256 (students \times features), and the model could suffer from the curse of dimensionality [29]. One potential solution to this problem would be to apply dimensionality reduction methods such as Principle Component Analysis (PCA) or feature selection, however, this is out of the scope of this study. Third, when $k = 32$, the LHM has the largest improvement over STFT in both L1 and L2. This result might indicate a relationship between the best performing k and the number of samples in the dataset.

The evaluation results of Experiment 2 are shown in Fig. 5. The first observation we can make is that both the designed and the SC features outperform the baseline features. This is in line with our expectations, as the baseline features are low-level instantaneous features that are not optimized to the task. Second, the proposed SC features achieve comparable performance to the designed features. The fact that SC features perform similarly to the designed features is encouraging, suggesting the possibility of deriving viable features through feature learning with minimum effort in feature crafting. Third, when combined with baseline features, both designed and SC features exhibit almost no improvements. There exist two possible explanations for this. On the one hand, it could be that these features do not add any information that is not

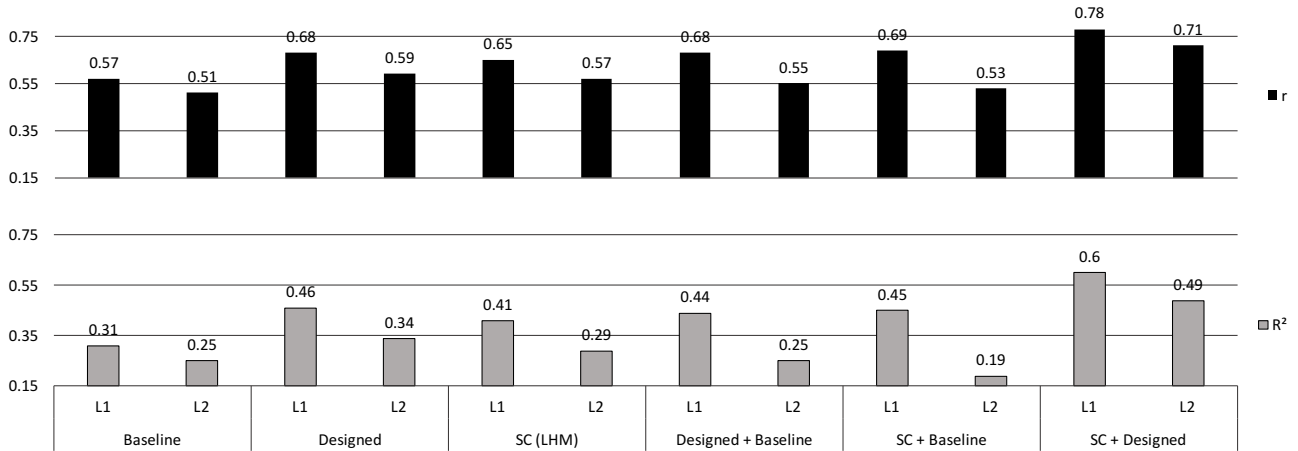


Fig. 5. Evaluation results for Experiment 2 (top) r (bottom) R^2

already in the other features. On the other hand, this issue could be similar to the situation in Experiment 1 when having a large k , as adding baseline features might induce the curse of dimensionality by introducing too many features to the current size of sample pool. Four, among all the tests in Experiment 2, the highest performance is achieved with the combination of designed and SC features. The result implies the effectiveness of SC features in capturing information that is non-redundant to the information provided by the designed features. This demonstrates the potential of using feature learning methods to complement designed features due to the learned features' ability to capture relevant information not or incompletely modeled by features designed with expert knowledge.

A general observation that can be made from all experiment results is the superior model performance for L1 over L2. As discussed in [10], musicality is an abstract but holistic measure of the performance, and it is therefore more likely to reflect the overall perception of the judges and is more consistent across the years.

V. CONCLUSION

This paper presents an unsupervised feature learning approach to derive features for assessing percussive instrument performances. Specifically, we propose to use a histogram-based input representation to SC in order to allow the sparse coding to take advantage of temporal rhythmic information. We could show that — for the task of performance assessment — this input representation outperforms an STFT-based input representation that is frequently used for feature learning approaches. The learned features perform comparable to expert-designed features for this task, and are able to capture task-relevant information that is not represented in the designed features, indicating the suitability of combining "traditional" feature design methods with feature learning approaches for optimal performance.

In summary, the contributions of this work are: First, it provides insights into the selection of input representations for feature learning in the context of snare drum performance

assessment, favoring representations inspired by domain knowledge over standard representations such as STFT. Second, the proposed learned features achieve comparable results with the designed features, demonstrating the viability of deriving competitive features with minimum effort in feature design. Finally, combining the designed features with the SC features, the highest performance can be achieved. This result suggests that learned features might be able to provide complementary information to the features designed with domain knowledge, further optimizing the performance of a given task.

Possible future directions of this work include:

- (i) Evaluate and compare the efficiency of different feature learning algorithms. Methods such as DBN [17] and denoising autoencoders [30] may provide new insights into the finding of the best feature learning strategy for automatic performance assessment.
- (ii) Adapt the proposed method to other types of instruments such as Brass or Woodwind instruments. The evaluation results on melodic instruments could lead to the refinement of the proposed feature learning scheme.
- (iii) Try to allocate more data. To further investigate the robustness and generality of this approach, more data is needed. Additionally, the increase in sample pool can also help the investigation into issues such as the relationship between dictionary size k and the number of samples. This might lead to a better strategy for selecting the best performing dictionary size.

Music Performance Analysis and assessment is a multi-faceted topic, and the traditional custom-designed features might not capture all information that is needed for a detailed analysis. Complementing the set of features with learned features is a promising direction that we intend to explore further.

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