PERFORMANCE RENDERING FOR POLYPHONIC PIANO MUSIC WITH A COMBINATION OF PROBABILISTIC MODELS FOR MELODY AND HARMONY

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ABSTRACT

We present a method to generate human-like performance expression for polyphonic piano music. Probabilistic models and machine learning techniques have been successfully applied to solve the problem of generating human-like expressive performance, given a music score. In case of polyphonic music, however, it was difficult to make models tractable and a huge amount of training data was necessary, because performance contexts and relationships of performance expressions are very complex. To overcome these problems, we propose a method with a combination of probabilistic models for melody and harmony. The experimental results show that the proposed method was able to generate fluctuations of performance expression parameters for polyphonic piano music such like human performers do. The results of the subjective evaluations are also reported which indicate that their sounds were human-like and had certain degree of musicality.

1. INTRODUCTION

Human music performances include expression which is not written in scores. This is one of the reasons why people prefer performed music by famous performers rather than performances without expression which can be directly rendered from the score itself. But the mechanism of human music performances is still not clear and therefore it is very difficult to generate human-like music performance expression automatically, given a music score.

However, if we can construct such a system, it will be useful for general users to obtain a copyright-free music performance automatically which can be used as a background music for their own original videos and home pages, for instance. In addition, it will be also useful for supporting music composition and education for not only professional musicians but also general users who have little knowledge of music. For example, users can obtain human-like expressive performances for their original songs very easily, even if they can not play a music instrument.

We focus on piano performances because there are many solo pieces for piano and performance expressions can be represented with relatively few parameters comparing with string and wind instruments. If we look at human performance expression for polyphonic piano music, we can observe that tempo, dynamics and performed note durations are changing permanently for melodies (Fig. 1) and observe that differences of note onset-time, velocity and performed note duration for harmonies (Fig. 2) . The problem of generating human-like expressive performance is to estimate fluctuations of these performance expression parameters, given a music score. However, it is a very difficult problem, because many relationships between score and its performance expression are not explicit.

To solve this problem, probabilistic models and machine learning from human performance expression have been successfully applied. In case of polyphonic music, however, it was difficult to make models tractable and a huge amount of training data was necessary, because performance contexts and relationships of performance expressions are very complex.

In this paper, we present a method to generate human-like expressive performances for polyphonic piano music by learning from human performance expression while avoiding data sparseness problems.

2. RELATED WORKS

Many computational methods for automatic music performance rendering have been proposed, such as rule-based expert systems, query-by-case methods and machine learning [2]. In this section, only probabilistic model based works which take advantage of machine learning from human performance expression will be briefly summarized.

S. Flossmann introduces *performance context* and propose a probabilistic model for monophonic melody[3]. The model is trained with a large amount of human performance expression recorded by two professional pianists, N. Magaloff and R. Batik. Performance expression is predicted by estimation of 3 parameters such as tempo, dynamics and articulations. K. Teramura propose a computational method for imitating music performance expression of famous pianists using Gaussian Process with a monophonic melody model[4]. For predicting tempo fluctuations, she considers periodical characteristics of tempo and reports good results for pieces in three-four time such as waltzes.[5].

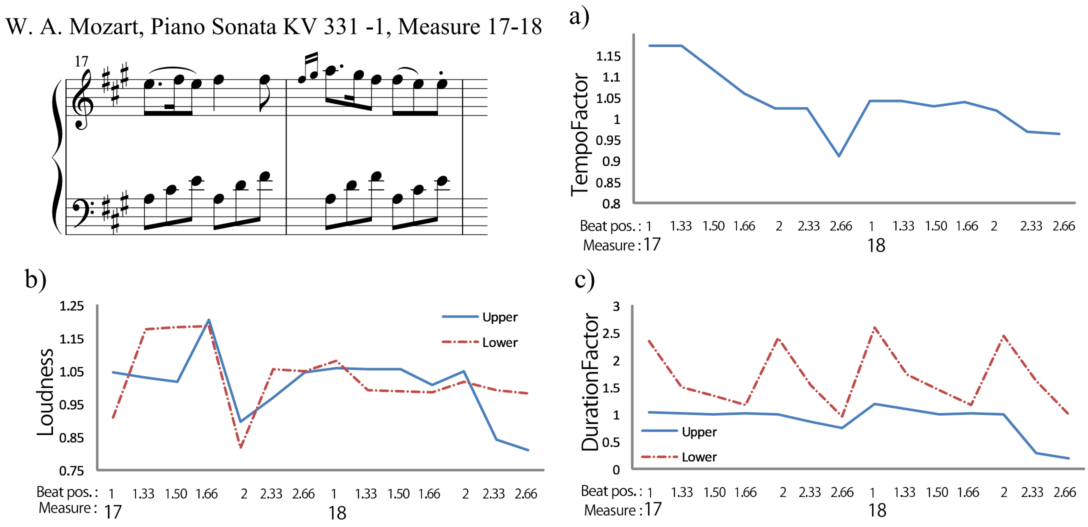

Figure 1. Performance expression for melody of a human performer (Ingrid Haebler, from CrestMusePEDB[1]). a) Fluctuations of instantaneous tempo which are calculated by the equation (1). b) Dynamics calculated by the equation (2). c) Fluctuations of performed duration which are calculated by the equation (3). These graphs show how human performance expression for melody looks like. Note that upper and lower outer-voices have different performance expressions.

These two works are based on monophonic melody models and they report quite good results for generating human-like performance expression. However, they don't discuss how to generate expression for polyphonic piano music.

There are some possible methods to generate performance expression for polyphonic piano music with monophonic melody models. For example, 1) generate performance expression of extracted main melody (e. g. soprano voice) from given music pieces and copy them to all other voices, 2) extract all voices and generate performance expression for each voice and combine them, 3) treat a polyphonic music piece as an one dimensional sequence of notes which is sorted by time and pitch orders.

However, these methods have some limitations. By 1) it is impossible to generate the characteristics of human music performance expression for polyphonic piano music which are mentioned above. 2) has a problem to extract all voices from given score which is very difficult. By 3) it is possible to generate different performance expression for each note even though input scores are polyphonic, however, its musical structure will be lost.

G. Grindlay proposes a Hidden Markov Model-based expressive music performance system and he discusses how to generate performance expression for accompaniment parts [6]. However, it is not possible to generate differences of performance expression of each note in case of harmony.

3. METHOD

In this paper, we present a method for performance rendering for polyphonic piano music with a combination of probabilistic models for melody and harmony.

Polyphonic piano music can be approximated with a combination of upper and lower outer-voices and harmonies. This is because human percepts outer-voices easier than inner-voices and inner-voices are related with sounds of harmonies[7]. In addition, upper and lower outer-voices don't have the same performance expression (Fig. 1).

Music performance can be regarded as a combination of global and local expressions. Global expression is the expression resulted from interpretation of expression marks such as *cresc.* and *rit.*. Local expression is the expression which has no expression marks for itself and is conditioned by local note-level contexts such as Fig. 1.

In this paper, we will focus on local expression, because we believe that it is important for *human-likeness* of performance expression. However, generating local expression is difficult, because relationships to their contexts are not explicit. To overcome this problem, a probabilistic model is applicable because it makes possible to capture some tendencies of relationships. If we assume that the relationships between contexts and performance expressions are probabilistic, then generating local expression can be regarded as an optimization problem to find the most probabilistic sequence of performance expression, given a sequence of performance contexts which are represented by rich score features.

Based on these discussions, we propose following strategy to generate human-like performance expression for polyphonic piano music:

Learning performance expression

1. Split music scores for training into right and left hands.
2. Extract sequences of the highest notes for right hand and sequences of the lowest notes for left hand. These two sequences are regarded as outer-voices. Extract harmonies for each hand.
3. Train left and right hand melody models with corresponding performance expressions of the extracted outer-voices.

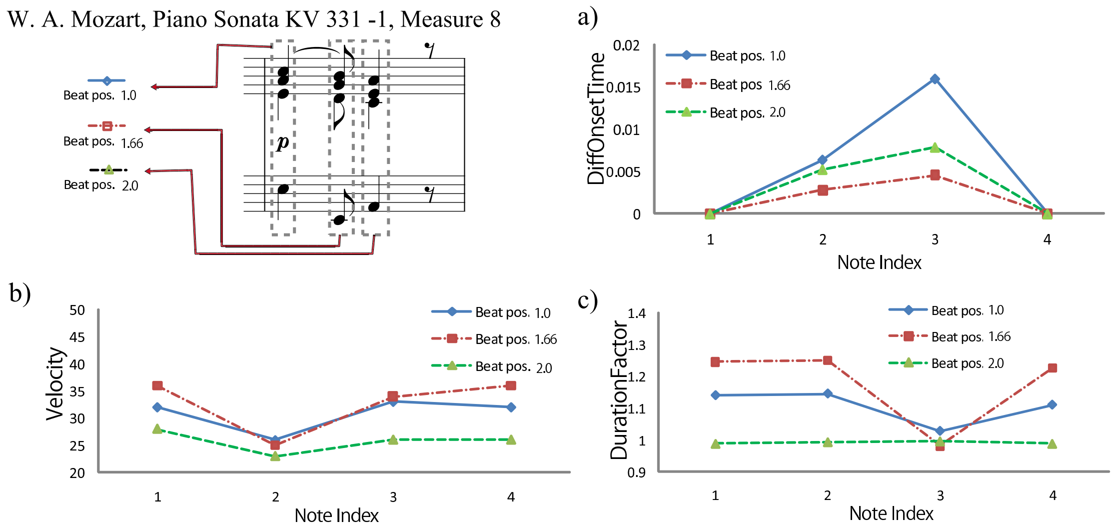

Figure 2. Performance expression for harmony of a human performer (Ingird Haebler, from CrestMusePEDB). Note index is an index of sorted sequence of notes in a given harmony (The first note is the highest note in a given harmony). a) Differences of onset-time calculated by the equation (4). b) Differences of velocity calculated by the equation (5). c) Differences of performed note duration calculated by the equation (6). These graphs show how human performs harmonies. Note that each note has a different performance expression to the others.

4. Train left and right harmony models with corresponding performance expressions of the extracted harmonies.

Generating performance expression

1. Split a input music score into right and left hands.

2. Extract a sequence of the highest notes and estimate its performance expression with the trained melody model for right hand. Extract a sequence of the lowest notes and estimate its performance expression with the trained melody model for left hand.

3. Estimate performance expression for right hand harmonies using the trained right hand harmony model and estimate performance expression for left hand harmonies using the trained left hand harmony model.

4. Combine the 4 estimated performance expressions.

On this strategy, we split scores into upper and lower outervoices and harmonies. Therefore, it is possible to generate human-like performance expression for polyphonic piano music with relatively simple score features and first-order Markov chain models using a small amount of training data.

Followings are details of melody and harmony model and its learning and estimation.

3.1 Melody model

3.1.1 *Performance expression parameters*

For melody model, 3 performance expression parameters are considered: instantaneous tempo, loudness and performed note duration. Fluctuations of each performance parameter can be modeled with first-order linear Markov chains if we assume that the current parameter value is conditioned only by its previous parameter value. In this way, we can avoid fast fluctuations which cause unnatural sounds.

Instantaneous Tempo

$$\mathrm{TempoFactor}_t = \log\left(\frac{\mathrm{Tempo}_t}{\mathrm{Tempo}^{\mathrm{scope}}_{\mathrm{avg}}}\right) \tag{1}$$

where $\mathrm{Tempo}^{\mathrm{scope}}_{\mathrm{avg}}$ is the average tempo of n_{t-3}, n_{t-2}, n_{t-1}, n_t, n_{t+1}, when n_t is the current note to perform.

Loudness

$$\mathrm{Loudness}^{\mathrm{melody}}_t = \log\left(\frac{\mathrm{Velocity}_t}{\mathrm{Velocity}^{\mathrm{scope}}_{\mathrm{avg}}}\right) \tag{2}$$

where $\mathrm{Velocity}^{\mathrm{scope}}_{\mathrm{avg}}$ is the average velocity of n_{t-3}, n_{t-2}, n_{t-1}, n_t, n_{t+1}, when n_t is the current note to perform.

Performed note duration

$$\mathrm{DurationFactor}^{\mathrm{melody}}_t = \log\left(\frac{\mathrm{Duration}^{\mathrm{real}}_t}{\mathrm{Duration}^{\mathrm{score}}_t}\right) \tag{3}$$

where $\mathrm{Duration}^{\mathrm{score}}_t$ and $\mathrm{Duration}^{\mathrm{real}}_t$ are nominal durations in given scores and performed note durations by human performers, respectively.

3.1.2 *Score features*

For performance expression of a melody, we assume that performance contexts are different for each performance expression parameter, even if the performing note is identical. Therefore, different score features are considered for each parameter (Table 1).

Table 1. Score features for melody model

Instantaneous tempo	**Loudness**	**Performed note duration**
-	Pitch	-
-	$\text{Duration}^{\text{score}}$	$\text{Duration}^{\text{score}}$
NoteInterval I, II, III, IV	NoteInterval I, II, III, IV	NoteInterval I, II, III, IV
DurationRatio I, II, III, IV	DurationRatio I, II, III, IV	DurationRatio I, II, III, IV
Metric I, II	Metric I, II	Metric I, II
Articulation Marks	Articulation Marks	Articulation Marks

In the score features, Pitch means an absolute pitch as MIDI note number and $\text{Duration}^{\text{score}}$ is a nominal duration in a given score. NoteInterval I, II, III, IV are the note intervals of pair $(n_{t-3},\ n_{t-2})$, $(n_{t-2},\ n_{t-1})$, $(n_{t-1},\ n_t)$, $(n_t,\ n_{t+1})$ where n_t is the current note, respectively. DurationRatio I, II, III, IV are duration ratios of each pair above. Metric is a variable which has a value from $\{very\_strong,\ strong,\ weak\}$ and Metric I, II are Metric of previous and current note, respectively. ArticulationMarks is an articulation mark such as *staccato*,*accent* and *fermata*.

3.2 Harmony model

3.2.1 Performance expression parameters

For harmony model, 3 performance expression parameters are considered: difference of onset-time, loudness and performed note duration. A sequence of parameter values which is sorted by pitch can be modeled with a first-order linear Markov chain to avoid a large difference of parameter values which causes an unnatural sound.

Difference of onset-time

$$\text{DiffOnsetTime}_i = \text{OnsetTime}_o - \text{OnsetTime}_i \qquad (4)$$

where OnsetTime_o is onset time of a note, which belongs to outer-voices, in a given harmony. OnsetTime_i is onset time of the current note to perform. DiffOnsetTime is a difference of onset-times, when a quarter note has a length of 1.0 (See [1]).

Loudness

$$\text{Loudness}_i^{\text{harmony}} = \log\left(\frac{\text{Velocity}_i}{\text{Velocity}_o}\right) \qquad (5)$$

where Velocity_o is velocity of a note, which belongs to outer voices, in a given harmony. Velocity_i is velocity of the current note to perform.

Performed note duration

$$\text{DurationFactor}_i^{\text{harmony}} = \log\left(\frac{\text{Duration}_i^{\text{real}}}{\text{Duration}_o^{\text{real}}}\right) \qquad (6)$$

Table 2. Score features for harmony model

Difference of onset-time	**Loudness**	**Performed note duration**
Pitch		
$\text{Duration}^{\text{score}}$		
NoteDistance		
OuterNote		

where $\text{Duration}_o^{\text{real}}$ and $\text{Duration}_i^{\text{real}}$ are performed duration of a note, which belongs to outer voices, in a given harmony and performed duration of the current note, respectively.

3.2.2 Score features

For performance expression of a harmony, same score features are considered for all 3 performance expression parameters (Table 2).

In score features, Pitch is an absolute pitch as MIDI note number and $\text{Duration}^{\text{score}}$ is a nominal duration in a score. NoteDistance is measured by a note interval between the note belongs to outer voices and the current note to perform. OuterNote is a variable which has *true*, if the current note is an outer note of the harmony and *false*, otherwise.

3.3 Learning and estimation

Because sequences of performance expression for both of melody and harmony are modeled by linear chain Markov models, any of HMM-like probabilistic models is applicable for learning and estimation. In the experiments, we employed Conditional Random Fields[8], which show better performances for input sequences represented by rich features. Both of melody and harmony models are trainable with Maximum Likelihood Estimation using Stochastic Gradient Descent algorithm[9] and performance expression can be estimated with Viterbi algorithm. To implement the proposed method, we used "crfsgd" package by León Bottou [1] .

3.4 Quantization of performance expression parameters

Performance expression parameters should be quantized into discrete values for learning and estimating performance expression, because CRFs are frameworks for predicting label sequences and therefore it is not able to estimate continuous values. In the experiments, the parameters were quantized into 32 labels with k-means algorithm. Initial values of the algorithm are given by random sampling from the prior distribution of performance expression parameters which is obtained from the training data and therefore a non-linear quantization preserving the prior distribution of performance parameter values is possible, for example, more probable values of performance expression parameters are quantized into small size bins.

[1] http://leon.bottou.org/projects/sgd

Table 3. Training data for experiment 1. 4 performances of 1 piece were used totally.

Piece	Performer
Piano Sonata KV331, 1st Mov.	Hiroko Nakamura
Piano Sonata KV331, 1st Mov.	Norio Shimizu
Piano Sonata KV331, 1st Mov.	Ingrid Haebler
Piano Sonata KV331, 1st Mov.	Lily Kraus

4. EVALUATION

To evaluate proposed method for generating human-like performance expression for polyphonic piano music, we conducted two experiments: for test pieces which are known to the implemented system and for test pieces which are unknown to the system. To evaluate human-likeness and musicality of the generated performance expression with the proposed method, we also conducted subjective evaluations for them.

In the experiments, we trained melody and harmony models with CrestMusePEDB ver. 2.3[1]. In the subjective evaluations, we used sound samples which are rendered with a sampling-based virtual instrument, "Garritan Instruments for Finale2009" from Garritan Libraries.

4.1 Experimental environments

Experiment 1 – For known pieces to the system In experiment 1, we evaluated the proposed method for known pieces to the system. Melody and harmony models were trained with 4 human performances of W. A. Mozart, Piano Sonata, KV. 331, 1st Movement (Table 3). As the test piece, we used the same piece. It is composed with several harmonies and therefore we can see, if the proposed method is able to generate performance expression for polyphonic piano music.

Experiment 2 – For unknown pieces to the system In experiment 2, we evaluated the proposed method for unknown pieces to the system. Melody and harmony models were trained with 14 pieces of F. Chopin which are performed by Vladimir Ashkenazy (Table 4). As the test piece, we used F. Chopin, Nocturne No. 10, Op. 32, 2nd Movement which is not included in the training data set. This piece was selected because melodies and harmonies are mixed and it is usually performed with profound expression.

4.2 Generation results

As the results of experiment 1, the common performance expression of 4 performers were learned and generated.

We mentioned that the upper and lower outer-voices have different fluctuations of performance expression to each other in case of human performances. Probably, this is because each voice has a different role, for example, the upper outer-voice is a melody and the lower outer-voice is an accompaniment. Fig. 3 shows that there are also differences between fluctuations of performance expression parameters such as loudness and performed note duration of upper and lower outer-voices in the generated performance expression with proposed method.

Table 4. Training data for experiment 2. 14 performances of 14 pieces were used totally.

Pieces	Performer
Prelude Op. 28 No. 1, 4, 7, 15, 20 (5 pieces)	V. Ashkenazy
Etude Op.10-3, 10-4, 25-11 (3 pieces)	V. Ashkenazy
Waltz Op. 18, 34-2, 64-2, 69-1, 69-2 (5 pieces)	V. Ashkenazy
Nocturne No. 2 Op. 9-2 (1 piece)	V. Ashkenazy

For harmony, we mentioned that human performance expression have different onset-time, loudness, and performed duration for each note. Probably, this is resulted by influences from the interpretation of the piece by performers and the characteristcs of their fingering. Fig. 4 shows that generated performance expressions with the proposed method also has different performance parameter values such as onset-time, loudness and performed duration for each note.

The fluctuations were not random, for example, performed durations of lower voice showed a certain pattern according to a given accompaniment pattern, for example, the lowest note A is performed as *legato*.

These results indicate that with the proposed method, it is able to automatically generate fluctuations of performance expression parameters for *known* polyphonic piano music, with certain degree of musicality.

From the results of experiment 2, we also can see that upper and lower outer-voices have different fluctuations of performance expression parameters. For harmony, all notes have different performance parameter values to each other (Fig. 5).

The fluctuations were not random, for example, tempo fluctuations showed a certain pattern according to measure borders (a tempo-arch was observed for each measure).

These results show that with proposed method, it is also able to automatically generate fluctuations of performance expression parameters for *unknown* polyphonic piano music, with certain degree of musicality.

4.3 Subjective evaluation

The experimental results show that the proposed method is able to generate meaningful fluctuations of performance expression parameters for polyphonic piano music. To evaluate their human-likeness and musicality, we have conducted subjective evaluations.

For the evaluations, we prepared 3 performance expressions which are generated with the proposed method: W. A. Mozart, Piano Sonata, KV. 331, 1st Movement which

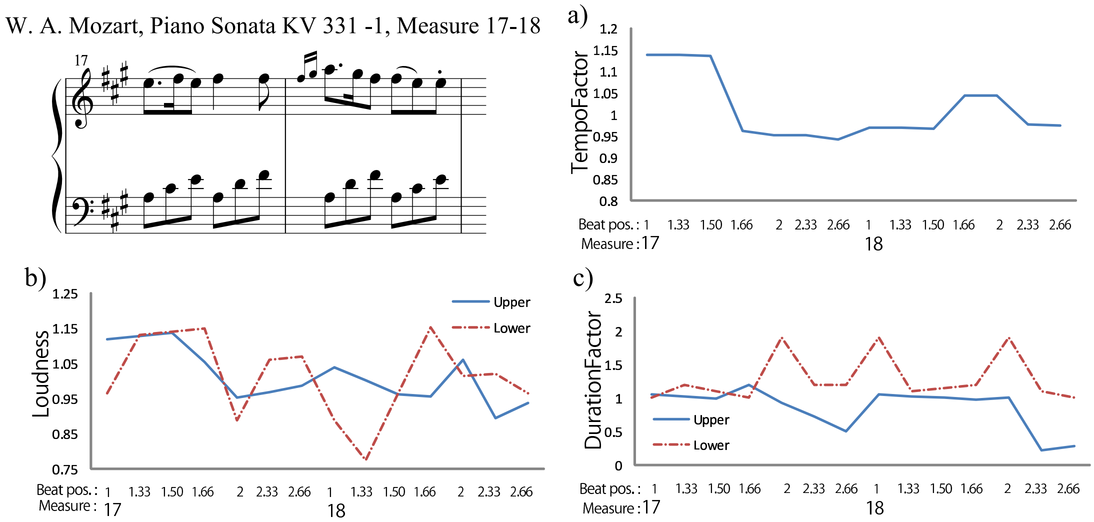

Figure 3. The results of experiment 1 (melody). a) Fluctuations of instantaneous tempo calculated by the equation (1). b) Dynamics calculated with the equations (2). c) Fluctuations of performed note duration which are calculated by the equation (3). These results show that the generated performance expression for melody with the proposed method have fluctuations of performance expression parameters such like human performance expression do and they are not arbitrary.

is the result of experiment 1, F. Chopin, Nocturne No. 10, Op. 32, 2nd Movement which is the result of experiment 2 and W. A. Mozart, Piano Sonata KV. 545, 3rd Movement whose performance expression is newly generated with the models trained with 6 pieces of Mozart's piano sonata [2] performed by M. J. Pires.

In addition, we prepared 3 more sound samples for each piece (total 12 samples): performance without expression, human performance expression, and performance expression for comparison. Performance expression for comparison has expression only for upper outer-voice and it is copied to the other voices and therefore upper and lower outer-voices have the same expression and each note of harmony also has the same expression. The purpose of preparing performance expression for comparison is to see if the proposed method considering polyphonic characteristics is effective to generate human-like performance expression for polyphonic piano music.

Human-likeness and musicality of each sound sample were evaluated by 25 participants [3] with 6 scaled scores, where 1 means "not human-like at all" and 6 means "very human-like" for human-likeness and 1 means "not musical at all" and 6 means "very musical" for musicality.

Fig. 6 shows the results of subjective evaluations. [4] In this figure, we can see that performance expressions generated with proposed method were evaluated that they sounded more human-like and musical for all 3 pieces comparing with performances without expression. In the cases of Mozart's Piano Sonata KV.331, 1 Mov. and Chopin's Nocturne No. 10, Op.32, 2nd Mov., participants evaluated them with the scores which are very closed to human performance expression (ANOVA indicates that thess differences are not significant). It means that performance expressions with the proposed method sounded human-like and musical for these pieces.

For Mozart's Piano Sonata, KV. 545, 3rd Mov., performance expression with proposed method obtained relatively low score comparing with human performance expression. This might be because for Mozart's piano sonata with fast tempo, global expression by interpretations of expression marks and musical structure is more important than local expression which are related with note-level contexts. In the experiment, human performance expression included both of local and global expressions and therefore performance expression with proposed method obtained such a low score comparing with human performance expression.

However, the averages of the 3 pieces show that performance expressions with proposed method obtained better scores than performance expressions for comparison and overall human-likeness and musicality of performance expressions with proposed method are most closed to human performance expressions comparing with other sound samples. Probably, this is because the proposed method is able to generate more profound expression than performance expression for comparison, especially for polyphonic piano music.

These results show that the proposed method is effective to generate performance expression for polyphonic piano music and its generation results sound human-like and have certain degree of musicality.

5. CONCLUSION

We proposed a method to generate human-like performances for polyphonic piano music with a combination of probabilistic melody and harmony models. With the experiments

[2] W. A. Mozart, Piano Sonata, KV279-1, 279-2, 279-3, 331-1, 545-1, 545-2. Note that KV545-3 is not included in the training data.

[3] 6 non-musicians, 17 hobby-musicians and 2 professional musicians participated in the experiment.

[4] Differences of average scores are tested by the Analysis Of Variance and its post-hoc test ($p < 0.05$)

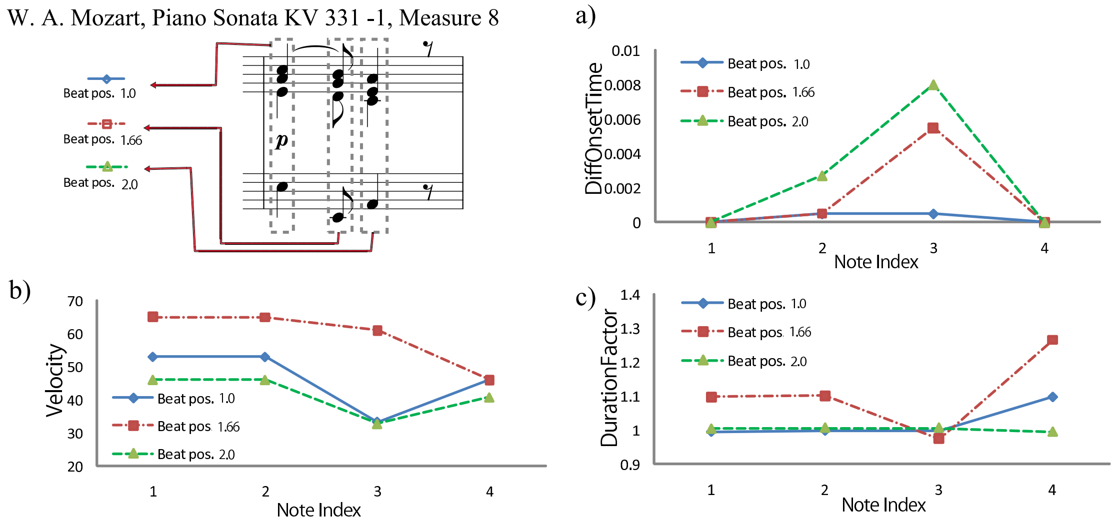

Figure 4. The results of experiment 1(harmony). a) Differences of onset-time calculated by the equation (4). b) Differences of velocity calculated by the equation (5). c) Differences of performed note duration which are calculated by the equation (6). These results show that the generated performance expression for harmony with the proposed method have different parameter values for each note, such like human performance expression do.

and the subjective evaluations, we showed that our method is effective to generate performance expression for known and unknown polyphonic piano music and they sound human-like and musical with profound expression.

Global expression by interpretations of expression marks and musical structure are also very important for human-like expressive performance. But expression marks are not easy to interpret, because each expression mark also has its certain performance context and therefore its interpretation is varying. As the next step, we will challenge to learn and estimate global expression to generate more human-like performances with more profound expression.

We believe that there is a possibility to learn personality of a specific performer through training models with his or her real performances. Therefore, we will experiment on the proposed method to see its ability to generate distinguish performance expression for each performer. This will be useful not only for searching a specific performer from a music database, but also for musicological researches of human music performances.

6. ACKNOWLEDGMENTS

This research is funded by CrestMuse Project [5] and a part of this research is supported by Samsung Scholarship Foundation [6].

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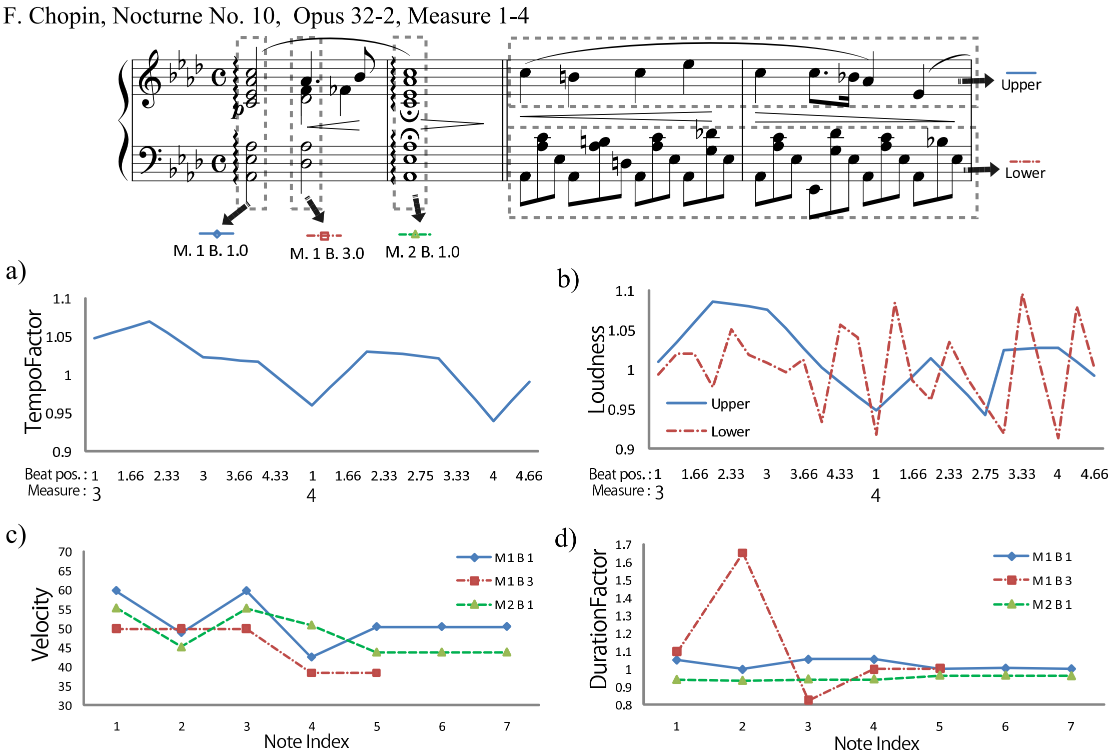

Figure 5. The results of experiment 2. a) Fluctuations of instantaneous tempo calculated by the equation (1). b) Dynamics for melody calculated by the equation (2). c) Velocity differences of the harmony notes which are calculated with the equation (5). d) Differences of performed note duration of the harmony notes which are calculated by the equation (6). Fluctuations of performed note duration for melody and Onset-time differences of the harmony notes are omitted due to space limitations.

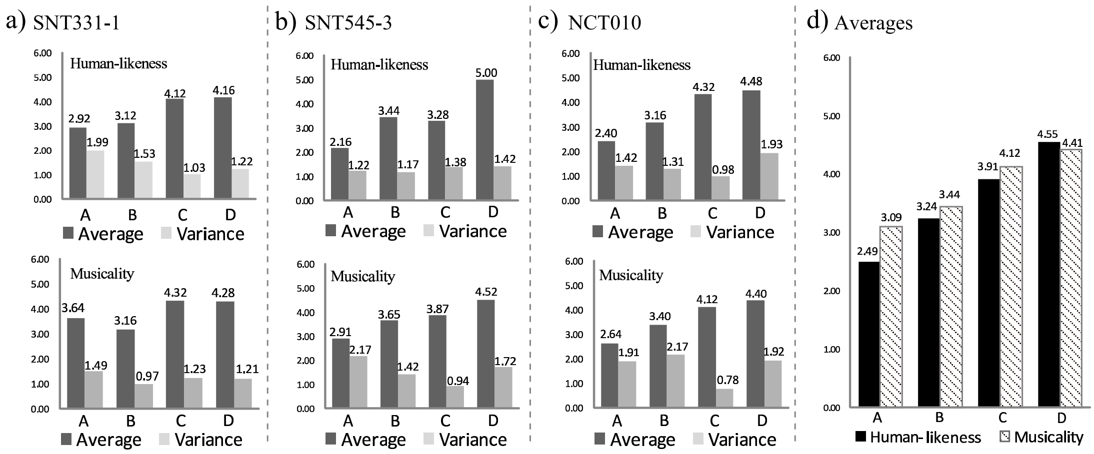

Figure 6. The results of subjective evaluations. A is performances without expression (deadpan). B is performance expression for comparison. C is performance expression with proposed method. D is human performance expression. Note that human performance expression includes local and global expression. a) shows the results for W. A. Mozart, Piano Sonata, KV. 331, 1st Movement and b) shows the results for W. A. Piano Sonata, KV. 545, 3rd Movement. c) shows the results for F. Chopin, Nocturne No. 10, Op. 32, 2nd Movement and d) shows the average human-likeness and musicality of the 3 pieces.