ENSEMBLE: A HYBRID HUMAN-MACHINE SYSTEM FOR GENERATING MELODY SCORES FROM AUDIO

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ABSTRACT

Music transcription is a highly complex task that is difficult for automated algorithms, and equally challenging to people, even those with many years of musical training. Furthermore, there is a shortage of high-quality datasets for training automated transcription algorithms. In this research, we explore a *semi-automated, crowdsourced* approach to generate music transcriptions, by first running an automatic melody transcription algorithm on a (polyphonic) song to produce a series of discrete notes representing the melody, and then soliciting the crowd to correct this melody. We present a novel web-based interface that enables the crowd to correct transcriptions, report results from an experiment to understand the capabilities of non-experts to perform this challenging task, and characterize the characteristics and actions of workers and how they correlate with transcription performance.

1. INTRODUCTION

Music transcription is the process of transforming the acoustic representation of a music piece to a notational representation (e.g., music score). Despite active research on automating this process, music transcription remains a difficult problem [1, 13] for automated algorithms, and equally challenging for human annotators, even those with formal music training. As a result, there is a lack of scalable methods for generating ground truth datasets for training and evaluating music transcription algorithms.

Crowdsourcing has demonstrated great promise as an avenue for generating large datasets. Recent work suggests that the crowd may be capable of performing tasks that require expert knowledge [24, 30]. In this paper, we investigate whether it is feasible to elicit the help of the non-expert crowd to streamline the generation of music transcription ground truth data. Specifically, we introduce a *semi-automated* system, which first extracts a note representation of the melody from an audio file, and then solicits the crowd to correct the melody by making small adjustments to the pitch, onset and duration of each note. Our

goal is to characterize the extent to which the crowd can successfully perform this complex task which typically requires musical expertise, describe the relationship between the actions that users take to correct transcriptions and their relationship to performance, and based on these findings, highlight specific challenges associated with crowdsourcing music transcription.

2. RELATED WORK

There are three threads of prior work relevant to our research: automatic music transcription, semi-automatic approaches to music transcription, and crowdsourcing the generation of ground truth data in music information retrieval.

In this work, we tackle a specific subtask of automated music transcription—automatic *melody* transcription. Given a polyphonic piece of music that has a clear melodic line, our goal is to transcribe the melody into a piano-roll like representation consisting of a sequence of non-overlapping notes, each with an onset time, duration, and a pitch value. While several approach have been proposed to date (see [27] and references therein), the task remains highly challenging and is still considered an open problem.

Given that fully automated transcription techniques are at the moment still limited, it is worth investigating how well machines aided by humans, or *semi-automatic* systems, perform at this task. [15] explored two methods in user-assisted transcription, where users provide information about the type of instrument and transcribe notes for some instruments. In the first case, users used spectra information from previously learned spectra models of the same instruments; in the second case, instrument spectra was directly derived from user labelled data. Their results showed that significantly higher transcription accuracies were obtained in the latter case. [8] introduced a human-in-the-loop model which solicits users to highlight notes to be extracted from the rest of the audio. In [29], users are asked to hum the melody to be extracted in a sound mixture. A source separation framework that incorporates prior knowledge has been proposed by [20], and the group has shown that the informed settings outperform the blind settings. Finally, recent work [16] elicits help from 30 users to provide note onsets and pitches as seeds to a semi-automated melody extraction algorithm, and found that experts and novices alike were able to contribute useful information. Likewise, Songle [12], a web service for music listening, provides users with the ability to modify a draft

transcription generated by an automated algorithm.

There has been a number of crowdsourcing experiments in music information retrieval that have investigated how to generate ground truth datasets for music tagging [17, 32] and music similarity judgments [33], and for more complicated music information retrieval tasks, such as the creation of emotionally relevant musical scores for audio stories [25]. These prior works found that the non-expert crowd can be incentivized to contribute accurate annotations for music.

3. ENSEMBLE

We propose Ensemble, a two-part architecture to the task of music transcription (Figure 1). The first part involves the task of automatically transcribing the notes of the melody from the audio signal of a music piece. The second part asks the crowd to fix and improve upon the automatically generated score.
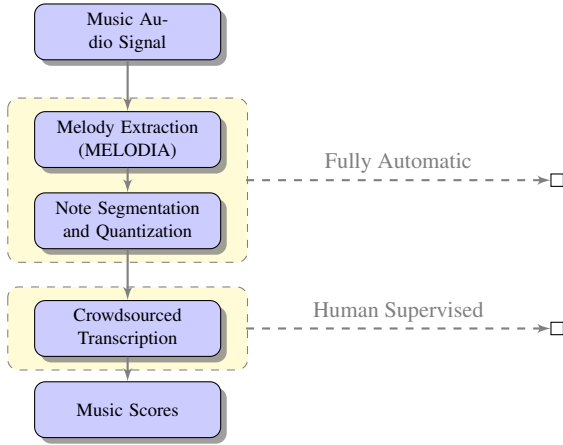

Figure 1. A semi-automatic architecture. Melody extraction and quantization is performed automatically, and this automatically generated transcription is then corrected by the crowd.

3.1 Automatic Melody Note Transcription

We employ a two stage process to produce an automatic transcription of the melody notes from the audio signal. First, we extract the continuous fundamental frequency (f_0) contour of the melody using the MELODIA melody extraction plugin [28]. Next, we quantize the extracted contour in pitch and segment it in time to produce a set of discrete notes. This is performed by means of the following set of simple heuristics: first, every f_0 value is mapped to its nearest semitone pitch assuming an equally tempered scale tuned to 440 Hz. The sequence is then smoothed using a median filter of 250 ms to avoid very short pitch jumps that can occur due to e.g. the presence of vibrato in the unquantized pitch contour. Finally, the sequence must be segmented in time into notes. Since MELODIA already estimates the start and end times of each voiced section (i.e. sections where the melody is present), we only need to

worry about pitch transitions within each section, and we segment each section into notes by simply starting a new note whenever the quantized pitch value changes from one semitone value to another. We impose a minimum note duration of 100 ms to avoid very short notes generated by continuous pitch transitions such as glissando. It should be noted that more advanced note segmentation algorithms have been proposed [10, 19], but since our goal is to evaluate the capability of the non-expert crowd to correct the automatic transcriptions (not solve automatic note segmentation), we do not require a state-of-the-art method for this study. Our complete melody note transcription script is available online [1].

3.1.1 Evaluation Metrics and Tools

To evaluate the agreement between two note transcriptions (i.e., automated/crowdsourced transcription against ground truth), we use the evaluation metrics from the MIREX [5] Note Tracking subtask of the Multiple Fundamental Frequency Estimation & Tracking challenge [2]:

$$\text{Precision} = \frac{|\text{correct estimate notes}|}{|\text{estimate notes}|} \quad (1)$$

$$\text{Recall} = \frac{|\text{correct estimate notes}|}{|\text{reference notes}|} \quad (2)$$

$$\text{F-measure} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (3)$$

An estimate note is considered to match a reference (ground truth) note if its pitch is within half a semitone (± 50 cents) of the reference pitch, its onset is within ± 50 ms of the reference note's onset, and its offset is either within ± 50 ms of the reference note's offset or inside a time interval whose duration is 20% of the reference note's duration centred on the reference note's offset, whichever is greater. MIREX also computes a second version of each metric where note offsets are ignored for note matching, since offsets are both considerably harder to detect automatically and more subjective: our ability to perceive offsets can be strongly affected by the duration of note decay, reverberation and masking [3, 18]. In light of this, and following our own difficulty in annotating offsets for our dataset, for this study we use the metrics that ignore note offsets, as we do not consider it reasonable to expect our participants to be able to accurately match the offsets when our expert was not certain about them in the first place. We also compute a more relaxed version of the metrics where the onset threshold is increased to 100 ms. All the metrics were computed using the JAMS evaluation wrapper for the `mir_eval` library [22].

3.2 Crowdsourcing Interface

Figure 2 depicts the interface that we designed for crowd workers to correct the music transcription. The interface

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[1] Omitted for peer-review.
[2] http://www.music-ir.org/mirex/wiki/2015: Multiple_Fundamental_Frequency_Estimation_\% 26_Tracking_Results_-_MIREX_Dataset#Task_2: Note_Tracking_.28NT.29
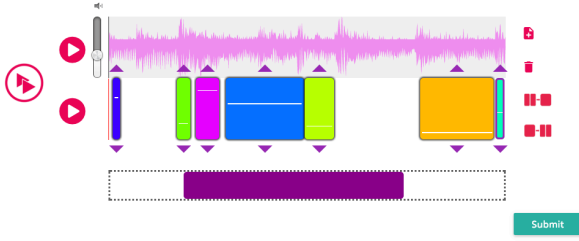
Figure 2. Screenshot of the note editing interface.

consists of two panels: the reference panel (top) and the transcription panel (bottom). The reference panel displays the waveform of the original music clip. The transcription panel displays the current note transcription; initially, this is the transcription automatically generated by the MELODIA-based transcription algorithm. Similar to many music editing software, the transcription panel uses rectangles to denote individual notes, height (and in our case, also color) to denote pitch, and width to denote duration. Workers are given controls to play the reference music clip and transcription separately, as well as simultaneously.

To edit the current transcription, workers can add, delete, split and merge notes. Notes can be added either by clicking on the "add note" button on the right panel or by double-clicking the area where the user wishes to add a note. Notes can be deleted by first clicking on the note, then either clicking the "delete note" button or tapping "backspace" on the keyboard. Adjacent notes can be merged by first clicking on the note and then clicking the "merge notes" button, which will merge the currently selected note with the immediate adjacent note to the right. Similarly, a note can be split into two notes by first clicking on the note and then clicking the "split note" button.

Pitch can be adjusted (by one semitone at a time) either by using the up and down arrows attached to each note, or by clicking on the note and then pressing the up and down arrow keys on the keyboard. Every time the pitch is adjusted the note is played back to indicate the new pitch. The note can be moved in time by dragging it left or right, and the onset and offset can be adjusted by dragging the note edges left or right. The purple bar at the bottom determines which segment of the audio/transcription is to be played. The bar is adjustable hence allowing the user to selectively choose the portion of the audio to focus on and compare the corrected transcription against.

4. STUDY DESIGN

In this work, our goal is to understand the extent to which crowdworkers can perform transcription correction tasks, which typically requires expertise. To do this, we conducted an experiment via Amazon Mechanical Turk to engage crowdworkers to correct the automatically transcribed melody from a 30 second excerpt of a song.

4.1 Data

For our experiments, we require a dataset of polyphonic music that has clear melodies (such as popular music) with ground truth annotations on a note level. Surprisingly, we found it hard to find suitable data. Most datasets with note annotations are comprised of music that does not contain an unambiguous melody (e.g. chamber music [7, 31] or solo piano [6]), or contain artificially synthesized audio data [9]. The two most relevant datasets, RockCorpus [4] and RWC-Pop [11] also turned out to be problematic: the former only contains pitch-class annotations for notes while the latter was problematic in terms of aligning the audio content to the provided MIDI annotations, which we found to be insufficiently accurate for the purpose of this study. Ultimately, we decided to create our own dataset.

To create the dataset, we selected 20 songs from the Million Song Dataset [2] which had a clear melody, in all cases sung by the human voice. For each song we obtained a MIDI file that was automatically aligned to a 30 s excerpt of the audio [23]. Using `pretty_midi` [21], we identified and separated the MIDI track containing the melody notes. The separated melody was then loaded into Logic Pro and manually corrected by one of the authors with formal music training to match the melody as accurately as possible, and finally converted to JAMS format [14]. Since transcribing a sung melody into a series of quantized notes is a task that contains a certain degree of subjectivity, the following guidelines were followed:

- The onset and offset of each annotated note should match the audio recording as accurately as possible.

- Pitch is annotated on an equally-tempered semitone scale tuned to 440 Hz.

- Every sung syllable is annotated as a separate note.

- Whenever the pitch of the melody is perceived to change by a semitone or more it should be annotated as a separate note, even if the syllable does not change, including embellishments and glissandos.

The same guidelines were communicated to crowdworkers in the tutorial preceding the experiment.

4.2 Participants

There were a total of 105 Turkers who participated in the study. Each Turker was assigned a randomly chosen 30 s excerpt. Each 30 s excerpt is sliced into ten 3 s music clips, and each Turker performed corrections on all ten clips, one clip at a time. The majority of the workers were from the United States. The entire task takes roughly 20-30 minutes, and workers were paid $5 in total. Since we wish to evaluate how well a layperson randomly drawn from the crowd can perform this task, we did not restrict the pool of participants by the level of their formal music training. Finally, our system ensures that each worker takes our study only once.

4.3 Procedure

To begin, workers watch a tutorial video, which shows how an expert corrects the transcription for a 3 s music clip. The tutorial guides new users on how to approach this task, by highlighting all of the functionalities of the interface and specifying the rules to follow when considering the correctness of their transcription. The tutorial is followed by a pre-study questionnaire, which asks workers about their music background, including the number of years of formal music training, a set of listening tests (i.e., listening to two consecutive notes and determining which one is higher), and a set of knowledge questions related to music reading (e.g., whether they are familiar with musical notation such as key and time signature).

Workers performed a series of 10 tasks using the note editor interface to correct the transcription of the melody of consecutive 3 s music clips. The reason we use short 3 s clip is that the results of a previous in-lab pilot test gave the impression that longer clips (10 s) resulted in too much cognitive load on the worker, rendering the task too overwhelming for them. Furthermore, Mechanical Turk workers are more used to performing a series of short, *micro*-tasks. In order to better understand worker behavior and intent, all interactions with the interface were recorded and saved in the database alongside the worker's corrected melody transcription.

After finishing the transcription, workers are asked to complete a post-study questionnaire, which asks them about their experience using our interface. In particular, we capture motivational factors using the Intrinsic Motivation Inventory (IMI) [26], a scale that measures factors related to *enjoyment* (how much workers enjoy the task), *competence* (how competent workers think they are at the task) and *effort* (how much effort workers put into the tasks). Workers are asked to rate how much they agree with a set of statements related to these three dimensions on a 7-point Likert scale. For each dimension, we then average the workers' responses (inverting the scores for the negative statements) and use the mean value as the summary statistic for that dimension. Finally, we ask workers to rate the difficulty of the task, as well as comment on ways in which the interface could be improved and the aspects of the task they found most challenging.

5. RESULTS

5.1 Q1: Can Crowdworkers Correct Transcriptions?

5.1.1 Worker Performance

To understand whether the crowd can improve the automatic melody transcription, for each 3 s music clip we compute the F-measure (ignoring offsets) of the automated and the crowd-generated transcription against the ground truth using two onset tolerances: ± 50 ms (*F-measure_50*) and ± 100 ms (*F-measure_100*, subplot). In Figure 3 we present the scores of the crowd-annotated transcriptions (green dots) against that of the automatic melody transcription (blue line) for both onset tolerances, ordered by the
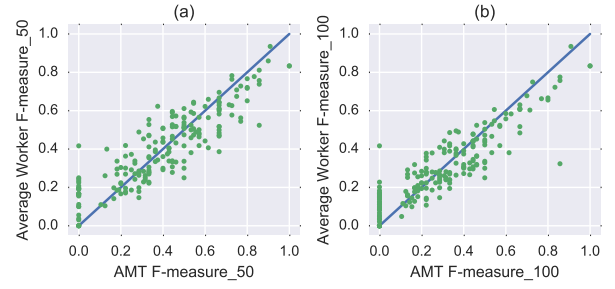

Figure 3. Worker F-measure against MELODIA-based transcription F-measure: (a) onset tolerance of ± 50 ms and (b) onset tolerance of ± 100 ms.

score obtained by the automatic transcription. Note that if a data point is located above the $y = x$ line it means the crowd-annotated transcription outperformed the automatic melody transcription, and vice versa.

In summary, the number of points above the line (N_A), on the line (N_O) and below the line (N_B) are $N_A = 85$, $N_O = 13$, and $N_B = 94$ for *F-measure_50* and $N_A = 88$, $N_O = 6$, and $N_B = 98$ for *F-measure_100* respectively. We see that when the F-measure of the automatic transcription exceeds 0.6, the majority of the points fall below the line, suggesting that the crowd has a hard time improving the transcription for clips for which the automatic algorithm already performs relatively well. Conversely, when the automatic transcription performs poorly the crowd is capable of making corrections that improve the transcription (i.e., the majority of the data points are on or above the line).

5.1.2 Worker Characteristics

The answers to the pre-study questionnaire are summarized Figure 4: (a) shows the distribution of the workers' musical expertise (T_1), (a) the number of pitch recognition questions answered correctly (T_2), and (c) the number of music knowledge questions answered correctly (T_3).

We see that the majority of the workers have little to no formal music training with 62% responding "None" or "1 year". 93% of workers answered at least two pitch recognition correctly and 63% answered at least two musical notation questions correctly. Given the variability in the scores achieved by the workers, we wanted to see if there was correlation between the workers' answers and their F-measure performance. To determine this, in Figure 4 (d), (e), and (f) we plot the workers' F-measure performance against the three separate topics T_1, T_2 and T_3 respectively. We also compute their Pearson correlation coefficients: 0.15, 0.15 and 0.23 respectively. Results show that the factor most correlated to the workers' performance is their understanding of musical notation. A possible explanation is that the person's proficiency with musical notation is a good indicator of their actual musical expertise. Self-reported expertise is not as good an indicator: this could be (for example) because the worker's musical training happened a long time ago and has since deteriorated through
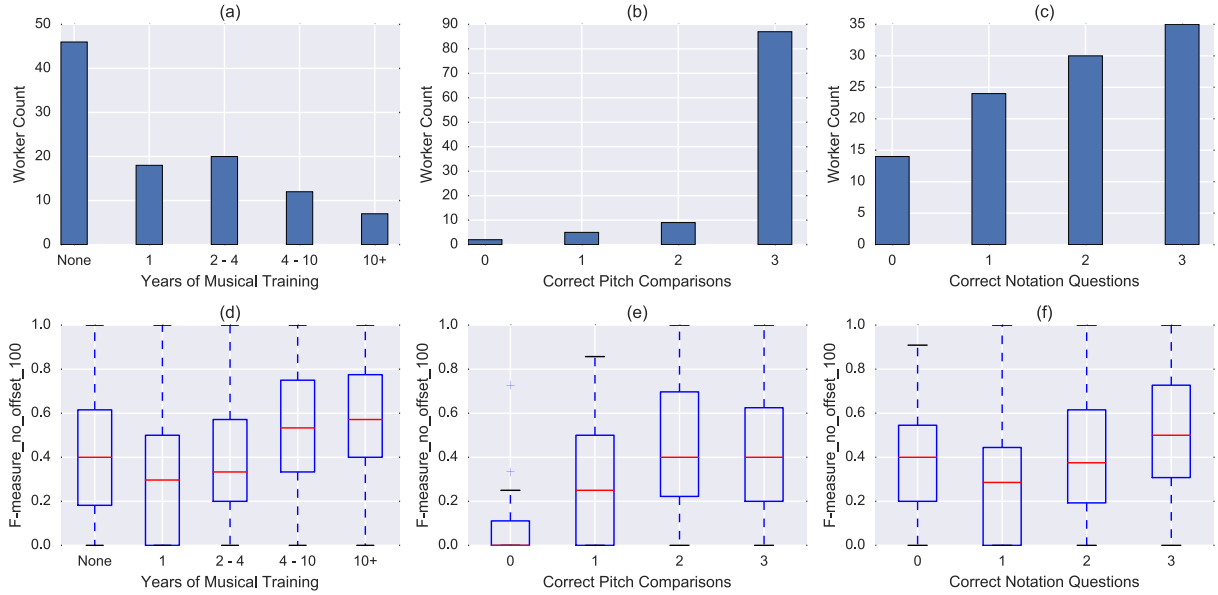
Figure 4. Pre-questionnaire results: (a) years of formal music training, (b) correctly answered pitch comparison questions, (c) correctly answered musical notation questions, (d) years of training vs. performance, (e) correctly answered pitch comparison questions vs. performance, (f) correctly answered musical notation questions vs. performance.

disuse (e.g., an adult took formal music lessons when they were a child but never again). Interestingly, the ability to differentiate pitches has the same correlation to F-measure performance as self-reported expertise despite the fact that melody transcription is dependent heavily on being able to identify pitches correctly.

The post-questionnaire shows that there are three main types of challenges. First, many workers ($\sim 20\%$) reported having difficulty matching the pitch of the transcription to the pitch in the audio (e.g., "It's hard to exactly match the notes to the melody."). There were several reasons cited, including *personal inexperience* (e.g., "I'm pretty sure I'm completely tone deaf. It was like trying to learn a foreign language."), *difficulty in separating the vocals from the background* (e.g., "Sometimes it was hard to hear the exact melody over the instrumentation.", "In my specific audio clips, the voice was very ambient and seemed to be layered in octaves at times. So, using only one tone to accurately denote pitch was slightly confusing.") and *difficulty with decorative notes* (e.g., "Vocal inflections/trails can be almost impossible to properly transcribe", "Getting all the nuances of the notes correctly, especially the beginning and ends of notes where the singer sort of "slides" into and out of the note.", "Some changes in tone were particularly difficult to find the right tone to match the voice. Mostly the 'guttural' parts of the singing.", "When someone's voice does that little vibrato tremble thing, it's almost impossible to accurately tab that out.").

Second, some workers reported difficulty with timing and rhythm, knowing *exactly* when things should start and end. For example, one musically trained worker said "Timing was incredibly difficult. I've been a (self taught) musician for 7 years so recognizing pitch wasn't difficult. The hard part was fitting the notes to the parts of the song in

IMI Factor	Mean	Standard Deviation
Enjoyment	5.87	1.46
Competence	4.15	1.79
Effort	6.30	0.93

Table 1. Mean and variance for each IMI factor.

the right timing. If there's anything I messed up on during my work, it was that." Finally, a few workers mentioned finding the task difficult due to the lack of feedback which would allow them to know if they were doing the task accurately ("It was hard to tell for sure if I was doing well or not.").

Many workers describe the interface as "intuitive," "easy to work", "well made," and "straightforward". The most requested functionality was the ability to play the audio at a slower speed, e.g., so that one can "catch grace notes or time beats more precisely." In practice this would require us to incorporate a time-stretching algorithm into the interface. Other requests include the ability to duplicate a note, undo previous actions, and get more training and feedback.

Overall, there seems to be an interesting paradox: workers find the task extremely challenging, yet enjoyable. For example, workers said "This is one of the best hits on Amazon mTurk.", "Getting it all to sound great is a challenge but fun", "Maybe I'm just not musically inclined, but even after going through several notes, it was still difficult for me to figure out whether or not they matched the singer's voice. Very challenging, but interesting too!"

The quantitative data also reflect this observation. Table 1 summarizes the average intrinsic motivational factors—enjoyment, competence and effort—over all workers. Results show that on average, workers enjoy the task (μ=5.87, σ=1.46), but at the same time, found themselves lacking
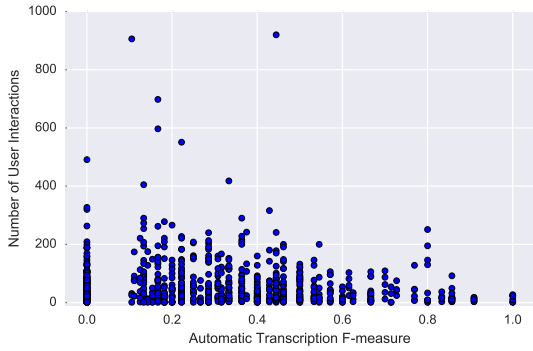
Figure 5. Number of user interactions vs. automatic transcription performance.

Action	Occur.	Action	Occur.
Play Both	16.1 (26.2)	Resize Play Region	6.3 (8.0)
Change Pitch	12.7 (12.1)	Move Play Region	3.9 (3.8)
Change Duration	9.6 (10.6)	Add Note	2.3 (1.9)
Play Wav	8.3 (13.2)	Merge Note	2.1 (1.8)
Change Onset	7.5 (9.0)	Delete Note	2.0 (1.4)
Play Transcription	7.2 (10.5)	Split Note	1.8 (1.1)

Table 2. Average occurrence (and standard deviation) of each worker action for all 3-second clips.

competence (μ=4.15, σ=1.79) in this task that they find effortful (μ=6.30, σ=0.93). In addition, they reported finding the task difficult (μ=5.57, σ=1.55).

5.1.3 Worker Actions

In order to understand more deeply how workers perform the transcriptions, we analyze the action log consisted of a list of coded user actions, including changes in onset, duration, or pitch (up or down), note addition, deletion, merge and split, as well as actions related to re-playing the original song and the transcription (play wav, play transcription, play both, resize-play-region, move-play-region).

In total, there were 53,411 user actions on the interface. The average number of user actions per clip is 60.3, with some workers making as few as 1 edit, and other workers making as many as 920 edits for a single clip. Figure 5 shows that the worse the initial automatic transcription, the more actions the Turkers took to make the corrections, which is quite intuitive.

Table 2 shows the average occurrence of each worker action performed over all transcription tasks. By far, the most frequently taken actions were "change pitch" (changing the pitch of a note up or down) and "play both" (playing both the transcription and the audio clip at the same time). The prevalence of the "change pitch, then replay" interaction potentially reflects workers' general difficulty in determining whether two pitches match. It also may reflect the fact that the interface currently allows only a semitone change a a time. Changing the onset and duration of a note occurred less frequently than changing the pitch, but much more frequently than adding or deleting notes. This behavior could indicate that workers are more inclined to modify a note that exists already in lieu of adding a new note. Together, the results suggest that pitch-matching may be the most challenging aspect of the task, and that workers may have an inherent bias to keep the number of notes in the automated transcription constant, while focusing instead on adjusting the pitch, duration and onset of existing notes.

6. CONCLUSION

In this paper we introduced Ensemble, a semi-automated system that leverages both algorithms and crowd to perform melody transcription. We reported the characteristics, performance and user-behavior pattern of a non-expert crowd of 105 workers for this complex task. For our experiment, workers were able to improve the initial transcription if it was poor, but found it hard to improve a transcription that was already mostly correct. Despite the crowd workers' sentiment that melody transcription is a difficult task, they also feel that it is a fun and interesting task that can hold their attention. We discover that there is indeed a correlation between the music expertise level of a worker and the F-measure performance of their transcription. Workers self-reported pitch-matching, while being the most frequent action, as also the most challenging aspect of the task.

Future work includes developing an aggregation algorithm that collates each worker's contribution to create a single transcription, discovering whether or not certain granularities (e.g., 1 s instead of 3 s clips) and decomposition (e.g., having workers specialize in a particular subtask, such as pitch changes) of the task can produce superior transcriptions, and developing new ways to identify the few skillful transcribers in the crowd and incentivize them to perform the task.

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