Downbeat Final Report

EECS 452
Fall 2019

Title of Project: Downbeat

Team members: Damon Anderson, Michael Halloran, Catherine Kenzie, Prakash Kumar, and Bryan Rabotnick

I. Executive Summary

The Downbeat project is a real-time drumming transcription system. The system processes a single audio track of a live performance on a drum kit and generates sheet music corresponding to what is being played. This process consists of two key algorithmic steps: classifying different pieces of the kit which were hit, and transcribing onset times to standardized music notation. The transcribed performance is displayed on a GUI which is updated in real time. The system offers additional visual feedback by flashing LEDs mounted on a 3D drum kit model corresponding to the pieces of the drum kit detected in classification. Pressing a playback button after the performance will prompt auditory feedback of the system's transcription. The system generates and plays an audio file using audio samples of the individual pieces of the drum kit.

Almost all of the primary goals for the project have been successfully met. These achievements include designing a stand-alone working prototype consisting of a Raspberry Pi 4 and an STM Nucleo F747ZI; implementing a setup procedure to calibrates the system with the spatial setup of the drum kit; generating a steady click track at a user-selected tempo within an appropriate range; supporting the classification of five distinct drum kit pieces and the transcription of sixteenth-note rhythmic subdivisions; providing two forms of real-time visual feedback via the GUI and the LEDs; and synthesizing the transcribed performance into an audio file for playback. The only primary goal which has not been achieved is classifying and transcribing drum rudiments, such as rolls and flams. The project has surpassed original expectations for layout and packaging. The processing components of the system are contained in a compact box which also serves as a platform for the 3D model. The box includes two buttons and a knob for user input as well as access to pertinent input and output ports.

Performance of the classification algorithm is dependent on the calibration process and the tuning of multiple parameters. The algorithm can reliably classify each piece of the kit in isolation, although its accuracy in identifying the hi-hat and crash cymbal decreases when either piece is played simultaneously with another piece. Performance of the transcription algorithm is dependent on one parameter which can be set to provide an optimal balance between precision and quantization error.

Downbeat Final Report

EECS 452
Fall 2019

Table of Contents

Downbeat Final Report

EECS 452
Fall 2019

I. Introduction

The Downbeat project is a real-time drumming transcription system. The system uses a single microphone to capture the audio of a live performance on a drum kit consisting of a kick drum, a snare drum, a rack tom, a hi-hat, and a crash cymbal.

The system processes the audio in real time and updates a GUI display with standardized sheet music notation corresponding to the performance. The system additionally lights up LEDs mounted on a 3D drum kit model which correspond to the pieces of the drum kit that were played. Furthermore, users can press a playback button to listen to the transcribed performance using audio samples of the individual pieces of the drum kit.

The system can be broken down into two general processing steps: classification and transcription. The classification step analyzes the audio signal captured by the microphone to determine which pieces of the drum kit were played and at what times these onsets occurred. Taking this information as input, the transcription step evaluates how these onsets times correspond to standard notation of musical rhythm.

II. System Architecture

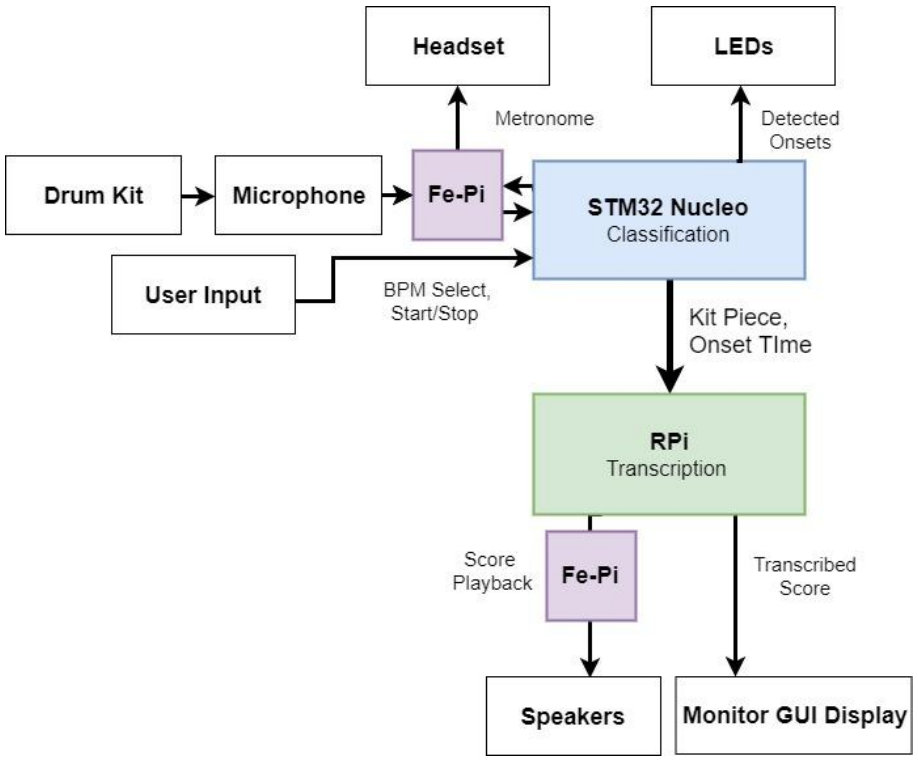


Figure 1: Block diagram of the Downbeat system.

Hardware Functionality

The Downbeat system's algorithms are implemented on a Raspberry Pi 4 (RPi) and STM32 Nucleo F747ZI. The Nucleo serves two primary purposes: to interface with both the user and the audio input, and to perform the complex signals processing steps needed in classification. A Fe-Pi Audio Z V2 codec is used to send the drum kit input from the microphone to the Nucleo. The Fe-Pi converts the incoming audio signal from the microphone to a digital signal that can be further analyzed. Also, this Fe-Pi is used to play a click track back to the user, functioning as a metronome to keep time. The click track is generated through the use of a hardware timer interrupt. The timer is configured to interrupt the program at a specific time interval based on the potentiometer value which corresponds to the desired tempo set by the user before drumming. When the interrupt is triggered, a pre-generated click sound is sent to the Fe-Pi DAC

and played back to the user through headphones. The Nucleo also interfaces with two buttons that are configured to hardware interrupts. A 'start/stop' button toggles the start of a processing session in which audio is accepted and the full processing chain is run. The first press of the 'playback' button prompts the synthesis and playback of an audio track based on the transcribed sheet music and made from recorded drum samples. Additional presses of this button prompts playback of the generated audio file so that the user can further compare the transcription to the original performance.

The Nucleo connects and controls multiple LEDs which are configured to light up as hits of the kit are detected by the classification algorithm. These are implemented through simple GPIO functionality. Finally, the classification algorithm is flashed onto the Nucleo and constantly run on incoming audio signals. The results of the classification algorithm are sent to the RPi via a UART connection.

Once the onsets arrive on the RPi, two major steps are run to generate the sheet music. First, the transcription algorithm is run to quantize the incoming hits. Once these results are available, the GUI rendering software is run to update the screen with the newly detected hits. When the program has not been started, updated BPM values are also received from the Nucleo and displayed on the screen allowing the user to choose the correct tempo. In the stopped state, the playback interrupts are also sent to the RPi to initiate the GUI synthesizing screen. An additional Fe-Pi is mounted on the RPi in order to perform recording and playback functionality. The recording functionality is necessary to record training samples for the classification basis matrix prior to runtime. The playback is sent via the Fe-Pi to speakers so that the user can hear the playback of the generated sheet music. Altogether, the RPi receives the results of classification by UART, converts these inputs to sheet music, and displays the results on the GUI.

Layout and Packaging

To improve user experience and increase physical robustness, most parts of the system including the RPi, Nucleo, Fe-Pis, breadboards, and wiring for hardware were encapsulated in a 200x120x75mm plastic box (see Figure 2). Drilled holes on the side of the box allows for connecting power to the processors, necessary inputs and outputs on the Fe-Pis, wiring to the external 3D model drum kit LEDs, and accessing the Nucleo's system reset button.

With the box, users cannot accidentally disconnect or otherwise disturb the setup and they can interact with the system in a more comprehensible way. The drilled holes on the lid of the box

closely fit two buttons and a potentiometer that are labeled with the parameter that they control. In the stopped state, the user turns the “BPM” potentiometer to select the tempo of their

Figure 2: Placement of hardware.

performance. The 3D model drum kit is secured to the lid of the box behind the buttons, providing visual feedback during the live drumming.

III. Classification

The Algorithm

The algorithm implemented in the classification step is modeled after the system proposed in [1]. This algorithm uses a separation-based approach to determine the onset times of drum kit hits. Separation-based approaches, also known as source-separation methods, separate a single-channel input signal into the distinct components that make up the signal. In this application, the input signal is the audio of the drum performance and the distinct components are the five pieces of the drum kit.

The input signal is captured by the microphone and sent through a Fe-Pi ADC at a bit depth of 16 bits and a sampling rate of 48 kHz. The digital signal is then stored in a FIFO structure on the Nucleo which continuously runs the classification algorithm. A Hamming window is applied to overlapping frames of the signal of a length of 1024 samples and a hop-size of 512 samples. The overlapping frames are converted to the frequency domain using the Fast Fourier Transform.

In order to reduce computational complexity, the signal's data is compressed by taking the summation of its spectral powers within a set of 25 frequency bands that coarsely partition the frequency spectrum. The frequency partitioning scheme initially used for classification was the Bark frequency scale. The Bark frequency scale separates the frequency range into 25 critical bands based off of human perception of auditory loudness. The Bark scale frequency band edges are [0, 100, 200, 300, 400, 510, 630, 770, 920, 1080, 1270, 1480, 1720, 2000, 2320, 2700, 3150, 3700, 4400, 5300, 6400, 7700, 9500, 12000, 15000]. This scheme was eventually adjusted to maximize the algorithm's resolution in the frequency range below 400 Hz. The adjusted frequency partitioning scheme band edges are [0, 44, 88, 132, 176, 220, 264, 308, 352, 396, 440, 510, 630, 770, 920, 1080, 1380, 1740, 2580, 4250, 6400, 7700, 9500, 12000, 15500]. A visual representation of this adjustment is shown in Figures 3 and 4. This adjustment was made because the kick drum, snare drum, and rack tom each have the majority of their acoustic energy concentrated within that range. A marginal improvement in the algorithm's ability to correctly distinguish between these pieces was observed upon adopting this altered partitioning scheme.

After performing this frequency-band summation, the algorithm uses Non-Negative Matrix Factorization (NNMF) to perform the source separation. NNMF uses an iterative heuristic to decompose a non-negative matrix X into two approximate non-negative matrix factors, the basis matrix B and the gain matrix G. In this application, X represents the time-varying spectral

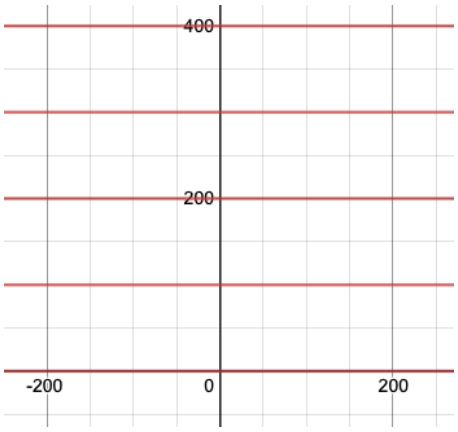


Figure 3: Bark frequency bands under 400Hz.

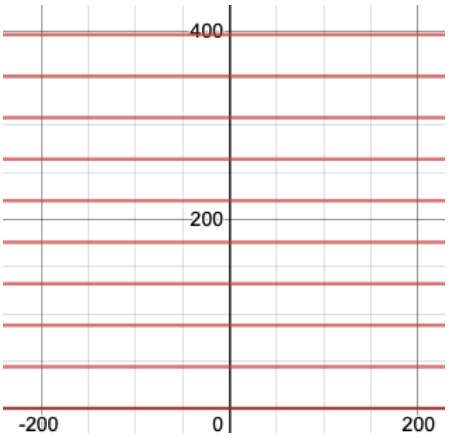


Figure 4: Adjusted frequency bands under 400Hz.

content of the drum performance, B represents "how the constituent components sound" and G represents the "time-varying amplitude envelopes" of each piece of the kit [2].

Instead of performing a blind factorization, this algorithm performs the NNMF using a fixed B matrix. This provides the algorithm with prior knowledge of the spectral content of each of the five pieces of the drum kit. In order to generate the fixed B matrix, recordings of each piece of the drum kit played once in isolation are required. These recordings are manually taken every time the drum kit and microphone are set up in order to minimize deviations in spectral content due to the acoustic environment as well as any physical changes in the relative placement of the kit pieces and the microphone.

Each of these recordings, or training samples, is processed before runtime in a manner similar to the drum kit performance. The primary difference is that the basis matrix factors of the training samples are calculated by taking the average over time of each of the 25 frequency bands instead of using NNMF. The decision to not use NNMF for these calculations was informed by comparisons between the two approaches during the prototyping phase as well as the method implemented in [2]. The resulting basis matrix factors of each training sample are single-column matrices that are stored as the columns of the fixed B matrix used for factoring the drum kit performance.

Using the fixed B matrix, the NNMF yields a gain matrix G consisting of values representing the acoustic intensity of each kit piece at that time frame. Figure 5 plots the resulting G values for the test drum beat pattern represented by Figure 6.

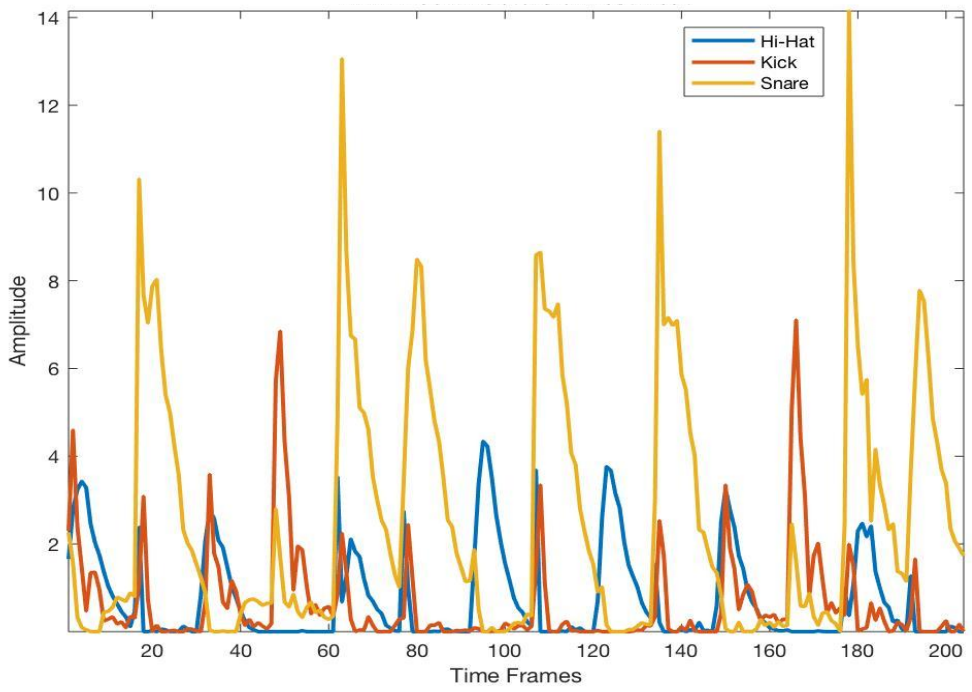


Figure 5: NNMF gain factors for test drum beat pattern.

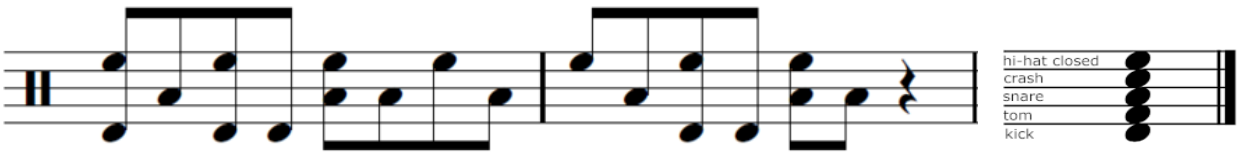


Figure 6: Test drum beat pattern.

NNMF is an iterative algorithm which typically continues to update the matrix factors until they reach a convergence as determined by a cost function. As noted in [1], however, "ignoring the cost function's value and forcing always ten iterations to occur, [has] no impact on the

performance" of the classification algorithm. Although observations during the prototyping phase indicated that ten iterations would not be enough to appropriately determine the G values, it was decided that 100 iterations would more than suffice. As such, the classification algorithm does not use a cost function to evaluate the convergence of the NNMF.

After running 100 iterations of the NNMF, a thresholding process is applied to the G values to determine whether or not each piece was hit. Since drum hits are characterized by a fast rise in acoustic energy, the G value for each piece must surpass a corresponding baseline threshold to be considered as a potential onset. Hitting one piece of the drum kit may also cause a sharp increase in the G value of another piece of the kit which can be erroneously mistaken for a real onset. In order to distinguish these false positive transients from the true positives, the classification algorithm evaluates the behavior of the G values after they reach relative peaks.

Multiple approaches were evaluated during the system testing phase to interpret these G values. Methods that were used but ultimately abandoned include evaluating the logarithm of the G values, the rate of their decay relative to their peak value, and the skew of the derivative of their decay. Eventually it was determined that using both the decay level and the sum of the half-wave rectified derivative of the logarithm of the G values would yield the best performance results. After 4 time frames have passed from a peak, if the G value of a piece exceeds its corresponding decay level threshold and if the sum of the half-wave rectified derivative of the logarithm of the G value over those frames is less than another corresponding threshold, then the classification algorithm determines that a true positive hit occured for that piece. The three threshold values for each of the five pieces of the kit were tuned through a manually iterative process based upon a subjective evaluation of the classification algorithm's accuracy. The threshold values were adjusted in an attempt to balance the algorithm's ability to correctly identify all true positive onsets with its ability to correctly ignore all false positive onsets. Plots of all of the considered methods as applied to the hi-hat G values for the test beat in Figure 6 can be found in Appendix A.

The classification algorithm supplies the transcription algorithm with information regarding which pieces are hit and the onset times as the hits occur. While testing the system, it was observed that the onset times drifted away from a steady tempo at a consistently increasing rate. Adjustments were made to the calculation of the onset times output by the classification algorithm in order to correct for this deviation.

Constraints and Solutions

The decision to use a single microphone to capture the drum kit performance imposed a significant constraint on the choice of a classification algorithms. As discussed in [2], the three general categories of algorithms that can be applied to this single-channel problem are source separation, template matching, and segment-and-classify. The choice of a separation-based NNMF algorithm was made due to its limited complexity and the existence of multiple academic reports detailing the advantages that such an algorithm offers in solving this problem. If multiple microphones were used, other potentially-simpler algorithms could be explored since each microphone signal could be responsible for classifying an individual kit piece or a subset of the kit pieces. That being said, the introduction of multiple microphones could also introduce additional complexity as a result of synchronization and computation requirements.

During the system testing phase, the average of three single-column matrices for a single kit piece generated by three different training samples was briefly used for the fixed B matrix in an attempt to account for variations in spectral content resulting from the intensity with which a piece is hit. There was no noticeable improvement in the system's ability to classify the drum kit performance, and so for the sake of simplicity only one training sample was used for each kit piece thereafter. It should be noted, however, that the quality of the system's classification of the crash cymbal is more dependent on the training sample used to generate its column of the fixed B matrix than the other four kit pieces are for their training samples. This is likely due to the fact that the crash's acoustic properties vary significantly compared to the other kit pieces depending on how it is struck. In particular, the system yielded its best results when the crash was struck lightly on the bell of the cymbal for the training sample.

Plans were initially made to develop and implement a noise filtering step in the classification algorithm due to concerns that environmental noise could negatively affect its performance. Ultimately, these concerns were alleviated and the noise filtering step was left out. The rationale for this decision is that having the microphone placed in close proximity to the drum kit greatly reduces the impact that even loud environmental noises might have on performance. Furthermore, only noises of a percussive nature would have a likelihood of affecting the algorithm since the algorithm's thresholding process is designed to only select sounds with percussive characteristics and because persistent ambient sounds would be accounted for in the training samples.

Testing and Results

The classification algorithm was tested by playing each piece of the kit individually and in various combinations 100 times at a constant tempo. The total percentage of correctly classified hits or pairs of hits are summarized in Figure 7.

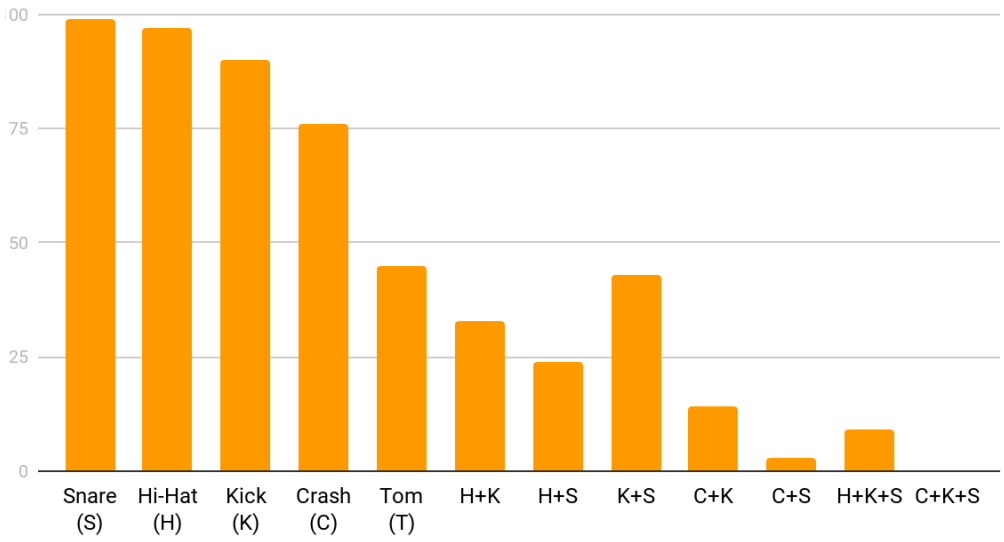


Figure 7: Total percentage of correctly classified quarter note hits at 120 BPM.

As these results indicate, the classification algorithm performs best when pieces of the kit are played individually. The performance for the crash and tom are less accurate than for the snare, hi-hat, and kick. This may possibly be due to the longer decay characteristics of the former pieces in comparison to the sharp transient nature of the latter pieces. Performance significantly deteriorates when multiple pieces of the kit are played simultaneously. This is primarily due to the algorithm's difficulty recognizing the hi-hat and crash hits, whereas it is able to fairly accurately classify the snare and the kick. The full results of this test can be found in Appendix B.

It should be noted that the algorithm's performance, and thus any test results, are highly dependent on the tuning of the G value thresholds. The test results presented in Figure 7 were recorded following a long process of tuning these thresholds to the point where they were qualitatively deemed to yield sufficiently accurate classification results. Additionally, the

algorithm's performance depends a great deal on the placement on the microphone relative to the drum kit. The results above were recorded after placing the microphone low to the ground, near the kick drum, and pointed up towards the snare. This position was settled upon because it was qualitatively observed to produce the best overall results for each of the five kit pieces. For comparison, testing results recorded using a different microphone placement are included in Appendix C.

These testing results illustrate both the current abilities and limitations of the algorithm as well as those inherent in the problem domain. While the algorithm does demonstrate positive potential, further study and testing are required in order to clearly distinguish algorithmic challenges from external issues and to refine the algorithm's performance. Drawing upon an intuitive understanding of how the system may be used could offer insight into smaller opportunities for improvement. As an example, some combinations of pieces, such as the hi-hat and crash, are unlikely to occur simultaneously. Knowing this, the algorithm could be modified so that the onset of only one of these pieces is classified at any particular time. Although this change would impose an artificial limit on what a user may perform, it has the potential to greatly improve the algorithm's performance.

IV. Transcription

The Algorithm

The transcription algorithm takes in hit onsets determined by classification and maps those inputs to standard drum kit sheet music. First, a terminology will be defined to help describe this process:

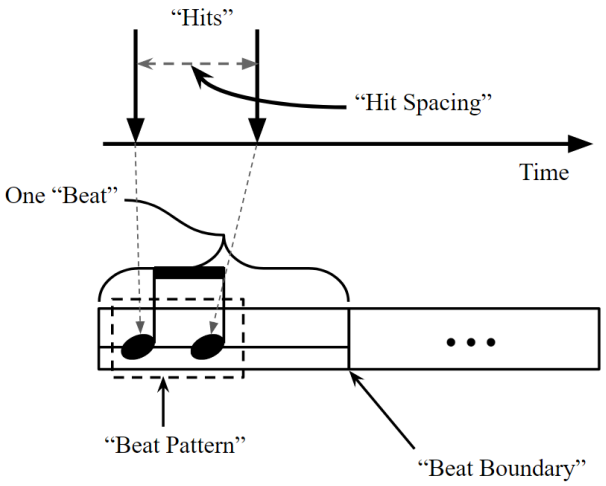


Figure 8: Example beat diagram.

- *Hit:* An onset of any instrument in the drumkit.
- *BPM:* The number of beats per minute.
- *Beat:* A unit of time that corresponds precisely to one quarter note at a given BPM.
- *Beat Pattern:* One possible combination of hits that occurs in a specified amount of time.
    - *Beat Pattern Length:* The "specified amount of time" noted above.
- *Beat Boundary:* The time of the start of a beat.
- *Resolution Limit:* The smallest recognizable partial that is considered by the transcription algorithm (e.g. 16th note, 32nd note, etc.).

- *Prior:* The probability that a given beat pattern occurs.
- *Hit Spacing*: The amount of time between two hits. If the hit is the first to occur following a beat boundary, the hit spacing is the amount of time between the hit and the beat boundary.

Before runtime, a set of possible beat patterns is decided and the prior associated with each beat pattern in that set is determined. During runtime, incoming hits are compared to the predetermined beat patterns, and the best pattern is calculated. The resulting beat patterns are sent to the visual feedback system that is described in detail in Section V.

Pre-Runtime

Before runtime, all possible beat patterns are listed and the likelihood of each is calculated. One challenge was determining what scale of beat patterns would be used. To illustrate this tradeoff, consider a beat pattern length of one beat. This set consists of patterns such as a single quarter note hit, two eighth note hits, an eighth note rest followed by an eighth note hit, etc. Now, assume that the limiting resolution of the system is sixteenth notes. Then, this set of beat patterns can be estimated by noting that each sixteenth note can be either 'on' (a hit) or 'off' (a rest) which means $2^4 = 16$ possible combinations are allowed. To fully calculate the set of beat patterns, the triplet pattern below the resolution limit (e.g. eighth note triplets in this case) must also be considered. Here, this would add 2^3 additional patterns, as well as a handful of patterns consisting of both eighth note triplets and sixteenth notes. Excluding the patterns with both triplets and sixteenths, a total of $2^4 + 2^3 = 24$ possible beat patterns are included. Now, as an alternate case, consider a beat pattern length of two beats. In this case, there are 8 possible sixteenth notes and 6 possible triplets. Then, the total number of beat patterns for a beat pattern length of two beats is approximately $2^8 + 2^6 = 320$, again excluding the patterns with both sixteenths and triplets. Although the beat patterns with both sixteenth and triplets are excluded, the important result here is that the total number of possible beat patterns will increase exponentially as a function of the beat pattern length. Since the algorithm is limited by real time computation constraints it is favorable to consider smaller beat length patterns. However, the system accuracy will decrease as the beat pattern length decreases because less information is available. This intuitive result will be justified once the method for *prior* determination is discussed. Then, there is a tradeoff between computational complexity and system accuracy associated with the predetermined beat pattern length.

For this project, a beat pattern length of exactly one beat was determined to be the most logical and realizable model. As shown above, the number of possible beat patterns for a beat pattern

length of one beat is on the order of 24 patterns. This is certainly manageable in real-time computation as 24 comparisons is negligible compared to the time scale of drumming, even at speeds such as 240 BPM. Also, it was theorized that most drumming rhythms would be distinguished over the scale of a single beat. One main consideration is whether triplets and sixteenth notes can be distinguished accurately, and since both of these partials occupy less time than one beat, both should be transcribed accurately. On the other hand, a set of quarter note triplets will occupy more than one beat length which means it will be difficult to transcribe these properly without a longer beat pattern length. Despite this, it was decided that a longer beat pattern length would result in significant computational delay and would not be worth the slight improvement in accuracy. Therefore, a beat pattern length of one beat was used for the transcription algorithm.

The next major challenge in beat pattern considerations was determining the resolution limit. In a similar calculation as above, it can be shown that the computation complexity increases exponentially as the resolution limit becomes finer. It was initially thought that 32nd notes would be needed to fully capture the complexity of typical rhythms because 32nd notes are often found in drumming. However, due to limitations in the classification algorithm's time resolution, it was later decided that 16th notes would be sufficient. At this stage, the set of allowed beat patterns is specified as those occurring over a beat pattern length of one beat with a resolution limit of sixteenth notes.

Next, the priors were determined for each possible beat pattern for use as a weighting factor. [3] proposes a method for tempo tracking in which the probability of note occurrence is proportional to $e^{-d(c_k)}$ where $d(c_k)$ is the number of bits required to represent the beat pattern c_k. In this project, the beat probability was calculated as the average of the base 2 logarithm of the denominators of each hit in the beat pattern. Consider a beat pattern consisting of two sixteenth notes followed by an eighth note, then the prior is calculated as shown:

$$\text{Beat Pattern Representation: } \left[\frac{1}{16}, \frac{1}{16}, \frac{1}{8}\right]$$

$$\text{Average } log_2\text{: } \frac{1}{3}(log_2(16) + log_2(16) + log_2(8)) = \frac{1}{3}(4 + 4 + 3) \approx 3.67$$

$$\text{Probability: } exp\left[-\left(\frac{1}{p_{const}}\right) * 3.67\right]$$

The p_{const} term is a constant that can be used to tune the prior of each beat during the pre-runtime phase. This method of prior assignment gave a realistic representation of what may be expected from a drummer; that is, quarter notes are very probable whereas sixteenth note patterns are less likely.

It should be noted here that for a larger set of considered beat patterns, the exponential distribution helps to discriminate against unlikely (more complex) beat patterns. The most complex beats will consist of several partials at the resolution limit. However, when the beat pattern length becomes smaller and approaches the resolution limit, the set of beat patterns will tend towards only containing the resolution limit partial. In this case, the prior will tend towards one for that limiting partial which means that no information can be gained by the pre-calculated prior. This is a concrete justification for the loss of accuracy associated with a decreasing beat pattern length.

Runtime Computation

After all of the pre-runtime considerations are computed, the transcription algorithm analyzes incoming hits by comparing the hit spacings to those in the possible beat patterns of length one beat. The hit spacings for each beat pattern in the set of possible patterns is known before runtime and this information is made available. During runtime, each time a hit is detected, the hit spacing is calculated. Whenever a new beat boundary is observed, the hit spacings from the last beat are compared to the hit spacings of every beat pattern in the set of available beat patterns. Since the number of hits is known, then beat patterns with just the same number of hits are considered. The differences between the known hit spacings and the calculated hit spacings are computed to determine how similar the incoming beats are to each possible beat pattern. Finally, given this information, the most likely beat pattern is determined by inverting the distance and multiplying by all note probabilities. The distances are inverted so that a smaller distance implies a large likelihood. Figure 9 graphically summarizing this process.

One additional feature of the algorithm is a "rounding" of beats to handle any errors around beat boundaries. Since beats are considered in discrete chunks, unexpected behavior can occur near the end or start of beat. For example, timing uncertainty associated with the system non-idealities will cause beats to be distributed in time. Then, for a hit expected to occur exactly at the start of a beat boundary, there is a chance that it will occur before the beat boundary thus appearing in the previous beat. To minimize transcription errors, a check is implemented to determine if a beat is very close to the start of the next beat. The distance of the hit onset from the next beat is compared to the distance to the actual quantized hit, and if the hit is closer to the

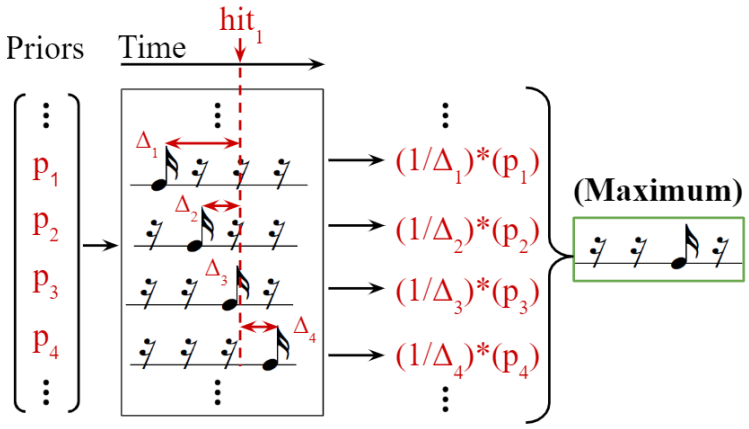


Figure 9: An overview of the transcription algorithm steps.

next beat then it is placed at the start of the next beat. This illustrates the challenge associated with analyzing discrete beat chunks as opposed to full inputs.

Constraints and Solutions

Due to the runtime and memory constraints imposed on the entire processing chain, some analytical precision had to be sacrificed in the transcription algorithm. In particular, most transcription algorithms found in literature process an entire set of hits and analyze the most likely quantizations of the pattern by generating a number of possible outputs. In real time processing, this depth of analysis cannot be achieved as only subsets of hits can be analyzed at a given time. As a result, lower accuracy levels should be expected as only subsets of the entire input can be analyzed as it is detected.

Additional constraints were placed on the tempo and meter assumed by transcription. Since quarter notes at 120 BPM are equivalent to eighth notes at 60 BPM, various accurate transcription outputs are possible if the tempo is not fixed. If a tempo is not specified then the transcription algorithm would be responsible for tracking and estimating the tempo in real-time. This task was deemed out of scope due to its theoretical complexity. Similarly, a variable meter implies that the transcription algorithm would have to estimate the most likely meter given the inputs. Again, this estimation process was ruled out and a fixed meter of common time, or four quarter notes per measure, was always assumed. Therefore, a fixed tempo and meter were always decided before runtime and the beat patterns, priors, and spacings were calculated based on these parameters.

Testing and Results

The method of priors and hit spacings showed promise in the prototyping phase due to its robustness in tunability and resistance to small errors. Since this method directly considers the absolute error between ideal beat patterns and incoming notes, it will always choose the closest note which makes it a robust method. In addition, the p_{const} discussed previously is easily tuned before runtime to optimize the accuracy. The p_{const} functions by adjusting the exponential decay so that a low p_{const} will cause the likelihood of more complex beats to be significantly lower than simpler beats and a high p_{const} will cause the beat patterns to be more similar in probability. At very high p_{const} values, all beats will be exactly the same likelihood, and at very low p_{const} values a quarter note will have roughly a probability of 1 and all other patterns will have a probability of 0. Somewhere between these extremes will be an optimal value where the minimum amount of quantization error occurs. The combination of absolute spacing comparison and prior likelihood assignments provides a method that is both robust and adjustable to the user's needs.

In implementation, the transcription algorithm was tested and tuned by playing the same rhythmic pattern at a constant tempo while varying the value of p_{const}. The pattern chosen and the results are shown in Figures 10 and 11, respectively.

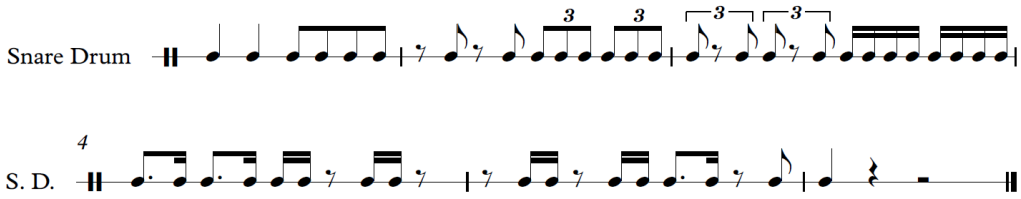


Figure 10: Sample beat pattern used for p_{const} testing.

The beat pattern was chosen to include a wide breadth of patterns that may be encountered. As observed in the results, at higher p_{const}values, significant errors are detected. In testing, it was seen that at these high values, some of the more simple patterns were often shifted into complex patterns because the equal likelihood of quarter notes and sixteenth notes meant that any timing uncertainty comparable to the length of a sixteenth note may cause incorrect quantization. In this way, the robustness of the algorithm was seen to be less in practice than in prototyping, and this is most likely due to a combination of user error, audio non-idealities, and classification timing

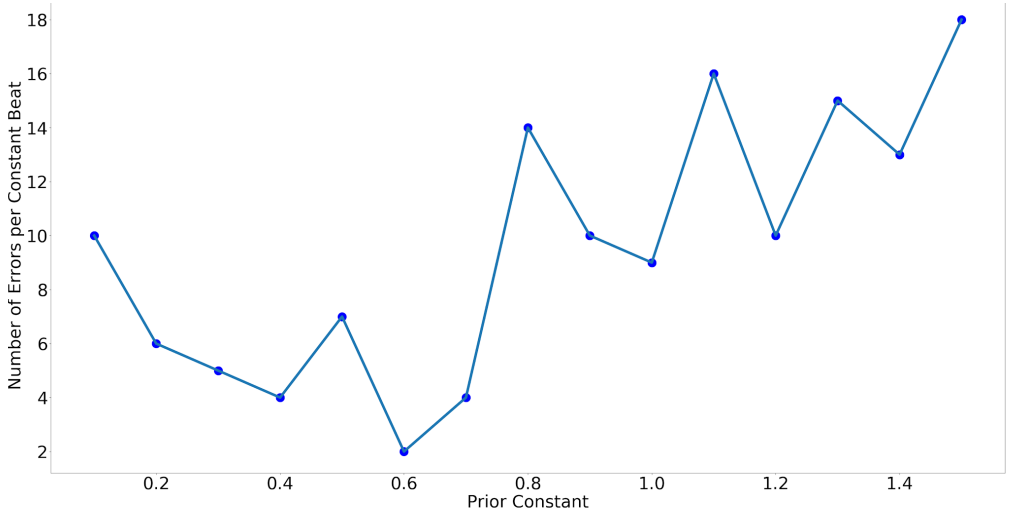


Figure 11: Transcription algorithm sensitivity to p_{const}.

uncertainty which may have induced larger errors than expected in the prototyping phase. Nonetheless, it was seen that, as the values of p_{const} were tuned lower, an optimum value occurred as the majority of rhythms were detected correctly. In the best case, two errors occurred and typically these were issues in distinguishing patterns such as  and  . This is unsurprising as these two beat patterns sound very similar, and slight variations in user playing may cause error in the algorithm. This underscores a fundamental limit of the algorithm which is that even to the human ear some rhythms sound very similar in certain contexts and therefore if the player cannot properly distinguish these rhythms then it will become very difficult for the algorithm to distinguish the rhythms since the algorithm can only reflect what the user plays. This testing showed the limits of the transcription algorithm and also revealed the potential accuracy of the algorithm if the p_{const} is tuned properly.

V. GUI

The Algorithm

The GUI is implemented using C and the Simple Directmedia Layer (SDL) [4]. In order to render sheet music notation, the Guido Music Notation library is used, as it is a powerful framework that supports the rendering of all music rhythms needed for the project, including triplets and sixteenth notes. Figure 12 offers an example of what the GUI looks like.

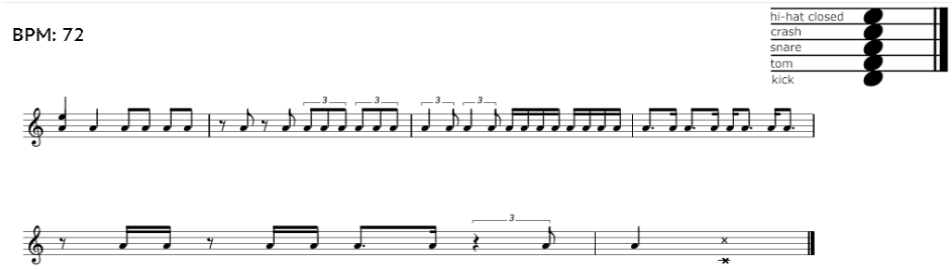


Figure 12: Downbeat GUI output when receiving real-time input.

The Guido library takes in a proprietary .gmn file that describes the notes and lengths from the output of transcription, and then creates an SVG markup file displaying the notes when opened in a browser. Guido renders this by using a special "Guido Font" library and placing notes, articulations, bars, and staff markings at specific x and y locations in the SVG. As SDL only has a simple image rendering library (SDL_image), it does not support rendering of SVG images and only supports more basic formats like .jpg and .png. In order to mitigate this issue, conversion from SVG to PNG is needed. Instead of re-developing an SVG parser, a Python implementation of SVG to PNG conversion is used called PyCairo. After converting to a PNG, the resultant image is then rendered on the screen. A diagram of this pipeline is shown in Figure 13.

The process of re-generating .gmn files, converting to SVG, converting to PNG, and rendering is necessary every time a new input is received. All the steps required in the GUI pipeline are also sequential, causing the system to slow down. To help prevent too much slowdown, a simple change to the system was made to only re-run the render pipeline when a new beat is received. Furthermore, all rendering is pushed to a separate thread from the transcription system, allowing

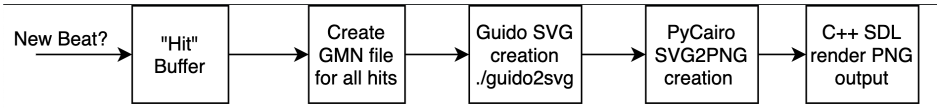


Figure 13: Guido rendering pipeline.

the UART communications from the Pi and the Nucleo to be separate from the necessary rendering calls.

Constraints and Solutions

Long Inputs

As the system is run for increasingly longer inputs, each new beat makes the rendered .gmn file larger, which in-turn makes the SVG take longer to render and the PNG take longer to convert. While initial results from small inputs showed that it would only take around 60ms to run the entire GUI pipeline, as the inputs got larger the lag became very noticeable. Because of the way .gmn files are made, there is no way to simply append to the file when a new beat is discovered; the .gmn files has to be re-generated for every new beat received, which contributes to the slowdown.

Furthermore, there is only so much real-estate on the screen the Raspberry Pi could output. As inputs got too large, the score displayed would run off the screen and be unreadable. Because of these two issues, it was decided that input sizes would be limited to 4 lines of Guido output, as any more lines would not be rendered properly. This reduces the need to develop any sort of system for the GUI to handle multiple pages of scores or scrolling, and also ensures that users will not have to wait for long periods of time after their last hit for the render to actually display. Lastly, this helps reduce the amount of time in the audio playback step, as smaller inputs mean a smaller final audio waveform to synthesize.

Playback Synthesis

Since the audio synthesis is written in Python using resource heavy packages like Numpy and Pandas, the playback synthesis step is considerably slower than other steps. Therefore, it is imperative for a visual feedback system to exist that shows the user that the system is in-fact working but just taking some time to complete the synthesis step. To do this, a loading bar was

added to the synthesis step (see Figure 14). Since the synthesis step is actually a Python script call, there is no straightforward way to identify how far along the progress of the script is to accurately display a loading time. Therefore, loading times are extrapolated by fitting a line to the delay given the input number of beats. Appendix D shows the considerations used to predict how far along the synthesis is.

Figure 14: Loading Bar during audio playback synthesis.

Complicated Inputs

As it is common for drum scores to consist of components with rhythms at any given beat, the possibility for some components to have various types of rests while other components are "hit" is very high. This results in the left image in Figure 15, where the Guido output is very cluttered and difficult to read. A considerable amount of processing is necessary to "hide" notes that are rests when there are other notes being rendered in the same beat. After this processing, the Guido output is much more parseable, as demonstrated in the right image in Figure 15. More information on how this parsing is done is shown in Appendix E.

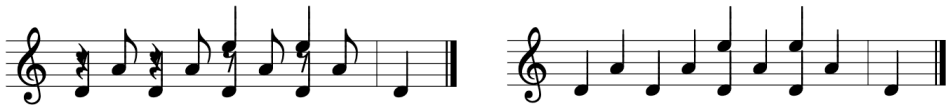


Figure 15: Difficult to interpret Guido (left) and the processed solution (right).

VI. Audio Playback

The Algorithm

The audio playback algorithm provides a means to playback the transcription results from a set of audio samples. The set of samples to generate the audio were originally used for training the classification algorithm. A Python script is used to handle the audio playback functionality. The playback algorithm works by first importing the Guido output in the form of a CSV containing onsets. This is imported initially as a dataframe from the Pandas software library. For N instruments, a mapping is then created between a set of integers from 0 to N - 1. From this mapping, it is then possible to extract the instruments classified at each onset into the form of a Numpy array, as well as doing likewise for the quantized onset times.

Once these critical data values have been extracted, it is then necessary to manipulate the data into a form which is amenable to the process of creating a new audio playback file. A new Numpy array representing the playback data is formed and initialized as a zeros matrix which has a length spanning the last onset's time plus the maximal time elapsed in any given recorded sample. These time lengths are measured in terms of samples, which is necessary to be consistent with the input and to produce an output at the same sample rate.

The playback audio is then created using the newly formed arrays for onset times, hit classifications, and playback. A loop is specified of range equaling the number of onsets. In this loop, a set of N conditional statements for each instrument are evaluated. If a given instrument was played, this triggers the conditional statement, which in turn triggers a for loop of range equaling the length in samples of said instruments recording. In this loop, the playback array is aligned at the onset time with the sample's first value, and start adding a coefficient augmented multiple of the sample to each space in the playback array within the length of the sample, corresponding to the onset start plus the current position in the loop.

Once this has been done for all onsets, the Numpy array representation of the transcribed beat has been successfully created, representing audio data in which each onset time corresponds to a triggering of the given instruments sample. One of the big draws for using Python in this algorithm is that once this array had been created, the SciPy library provides a function call which allows the array to be encoded into the .wav audio format.

Constraints and Solutions

Once the base playback algorithm has been established, challenges included mixing the samples when creating the playback file. Before determining the appropriate coefficients the sound quality of the playback was suboptimal. It is necessary to apply a coefficient to all instruments which scales the samples to a small fraction of the original data values, as too much overlap distorts the file. Then it is necessary to optimize the coefficients with respect to one another such that the mix is pleasing to the ears. To put this into perspective, the kick's coefficient is five times that of the snare, which in turn is twice that of the hi-hat. It is also necessary to add the function call to the C codebase to trigger this playback, and it is pertinent to ensure that the output .csv is available when this call is made.

VII. 3D Printed Drum Kit

To create a compelling display for presentations, a 3D model drum kit was printed with color coded LEDs mounted on the pieces of the kit. Numerous kit designs were considered, some requiring greater preprocessing, which could be accomplished with a program like Meshmixer. Ultimately, there were many issues to consider when sending the design to print, utilizing the Cura software and the Ultimaker printer in tandem. The desired 3D model is rather intricate and has a multitude of pieces aside from just the drums and cymbals, such as mounting components, pedal hardware, and stands. The relevant hardware components were printed and then anything that required mounting was manually attached.

Constraints and Solutions

The biggest constraint in regards to 3D printing was only being able to reserve one printer for one day. This is particularly challenging because 3D printing is a time intensive process, and if satisfying results were not obtained from the first print, an alternative option would likely have had to have been considered for the presentation display. This necessitated scaling down all of the drum kit pieces intended for use, transforming orientation such that it was possible to fit all of our kit pieces onto the 8x8x8" print bed, while providing adequate support while printing, which is vital to the integrity of any given piece.

It was also necessary to ensure that there was no spillover of resin from any one piece to another, requiring careful placement in the testbed model within the Cura software. Finally, tradeoffs were made in regards to print quality versus print time. Fortunately, Cura provides a multitude of functionalities for previewing prints and made it possible to get a good idea of the final result while printing.

The 3D print was ultimately successful, and the next step of attaching the LEDs to the constituents of the kit was in order. LEDs for one instrument were soldered in strings to a positive and negative wire. Then, for each instrument these LED strings were hot glued to the 3D print. The outgoing wires were all routed together into the box to be connected to their respective GPIO pins.

VIII. Summary of Constraints

User error and variability in drumming speed and intensity needed to be considered when implementing the system's algorithms. The three types of classification thresholds for onset detection were selected and tuned in order to optimize the algorithm's performance for what was considered to be the most likely level of variation in user performance. Similarly, the transcription p_{const} value was set to minimize error that may arise from the algorithm and not from the user. Although both of these decisions reduces the system's ability to properly handle complex user input, this limitation was deemed appropriate given the improvements that they yielded for the average use case.

Additional design compromises that were made include limiting the tempo step size to three of four beats per minute and synthesizing the audio for playback after the performance only if the user selects to do so. Each of these compromises has a practical justification. The limitation of the tempo step size was due to noise inherent in the potentiometer used to set the tempo which could produce errors in the transcription algorithm if this restriction was not imposed. The playback file is rendered using a Python script which is fairly slow. It makes sense that this script is called only when prompted by the user after the performance since it would otherwise add significant latency to the process of updating the transcription display.

IX. Milestones

Milestone 1

Goals for the project which were set for and achieved by Milestone #1 include prototyping the classification and transcription algorithms in Matlab; taking separate recordings of the five drum kit pieces and appropriate environmental noise and using combinations of the kick, snare, hi-hat and noise recordings for testing the classification algorithm; producing a mock-up of the GUI visual feedback display; and determining the optimal combination of components for implementing the system architecture.

While working in preparation for Milestone #1, it was decided that the noise filtering step of the classification algorithm would not sufficiently improve the algorithm's performance in order to justify its inclusion. It also became clear that both algorithms' accuracy, memory usage, and inherent limitations could only be properly assessed once they were implemented, tuned, and tested on the system's hardware. Although mock-ups of the transcription playback and the 3D model visual feedback were not completed by Milestone #1, they were both finished within the two weeks following Milestone #1.

Milestone 2

All goals set for Milestone #2 were achieved in time, which included completing a fully functional end-to-end system and designing a draft of the poster required for Design Expo. In between Milestone #1 and Milestone #2, it became apparent that the system's memory usage did not produce any tradeoff with the accuracy of the system's algorithms. It was also decided that rudiments could not be reliably classified using the current approach. Instead of pursuing this goal by implementing a new classification algorithm, this goal was abandoned in favor of supporting the classification of distinct drum onsets performed at tempos of up to 240 beats per minute.

X. Demo

Prior to demonstration at the Design Expo and at the final presentation, the components of the system were connected and the drum kit and microphone were arranged in a standardized manner on a 4x6' rug. The rug was used both to reduce any undesired acoustic reflections from hard floor surfaces and to set exact markers for the placement of the drum kit and the microphone stand. Once set up, new training samples were recorded to generate a fixed B matrix for the classification algorithm and the various classification thresholds were adjusted to optimize its performance.

Demonstration of the project involved a member of the team showing observers how to set the system's tempo, start and stop the system's transcription process, and play back the transcription results. The team member would play the kit to demonstrate the system's ability to recognize each of the pieces of the kit, as verified by the flashing LEDs mounted on the 3D model and the notation generated on the GUI monitor. Observers were encouraged to take a turn playing the drum kit so that they could independently evaluate the system's performance.

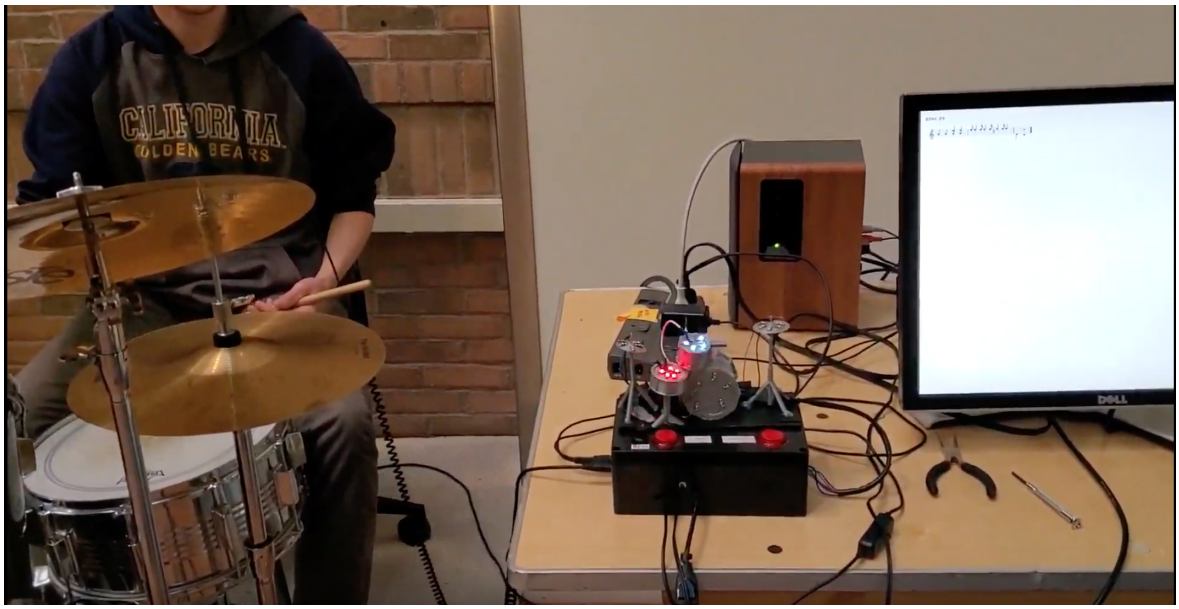


Figure 16: Photo of Downbeat setup at Design Expo.

XI. List of Parts

- Parts from the lab
  - STM Nucleo F747ZI
  - Raspberry Pi 4
  - Fe-Pi Audio Z V2 codec (2)
  - Power strip
  - Jumper wires
  - Mini breadboard (3)
  - 3.5mm male to dual RCA male cable
  - Tape
  - Wires
  - RPi cables/converter for HDMI
  - Monitor
- Parts purchased for the project
  - 200x120x75mm plastic box
    - https://www.amazon.com/LeMotech-Plastic-Electrical-Project-Junction/dp/B07D23BF7Y/ref=sr_1_11?keywords=black+plastic+box&qid=1574352593&sr=8-11
  - 30mm button (5)
    - https://www.adafruit.com/product/473
  - Panel Mount Right Angle 10K Potentiometers
    - https://www.adafruit.com/product/2046
  - Adafruit LED Sequins (5)
    - https://www.adafruit.com/product/3377
  - 3D-printed drum kit model
    - the reservation fee for using a 3D printer in the Duderstadt Center's Fabrication Studio was covered by the team budget. https://www.thingiverse.com/thing:1229824
- Parts provided by the team
  - Drum kit consisting of kick drum, snare drum, rack tom, hi-hat, and crash cymbal
  - Drum sticks (2)
  - 4x6' rug
  - Shure SM58S cardioid dynamic microphone
  - Samson MK10 boom microphone stand

- 20’ XLR cable
- Samson MDR1248 12-channel analog audio mixer
- Technics RP-DJ1200 headphones
- Edifier R1280T powered speaker

XII. Contributions of each member of team

Team member	Contribution	Effort
Damon Anderson:	Transcription, Hardware/Integration	20%
Michael Halloran:	Classification, LEDs, Audio Equipment	20%
Catherine Kenzie:	Classification, Hardware/Integration	20%
Prakash Kumar:	Transcription, GUI, Hardware	20%
Bryan Rabotnick:	Playback, 3D Printing, Classification	20%

XIII. References and citations

[1] G. Papanikas, "Real-time Automatic Transcription of Drums Music Tracks on an FPGA Platform," MSE dissertation, Dept. Informatics Mathematical Modelling, Univ. Denmark, Lyngby, Denmark, 2012.

[2] C. Dittmar and D. Gärtner, "Real-time Transcription and Separation of Drum Recordings Based on NMF Decomposition," in *Proceedings of the 17th International Conference on Digital Audio Effects (DAFx)*, 2014.

[3] Cemgil, A. T., and B. Kappen. "Monte Carlo Methods for Tempo Tracking and Rhythm Quantization." Journal of Artificial Intelligence Research 18 (2003): 45–81. Crossref. Web.

[4] "About SDL." *Simple DirectMedia Layer - Homepage*, https://www.libsdl.org/.

XIV. Appendices

Appendix A: Classification Plots

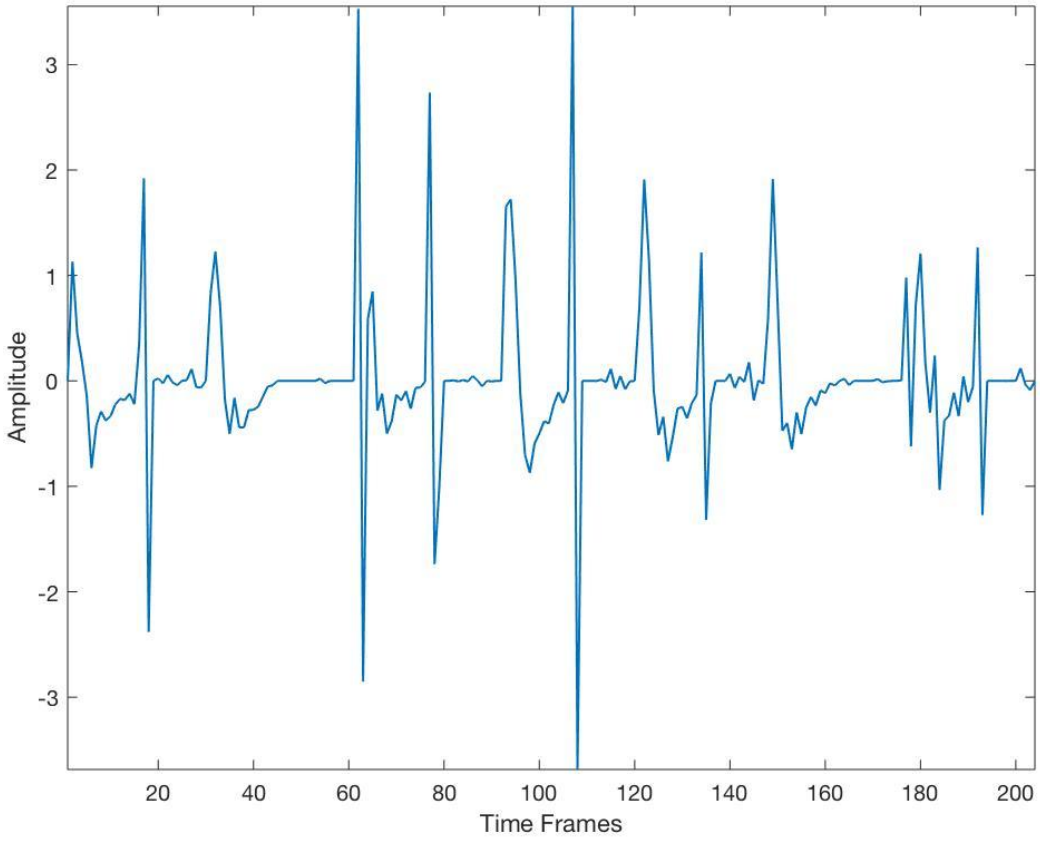


Figure A.1: Derivative of the hi-hat G values for the test drum beat pattern.

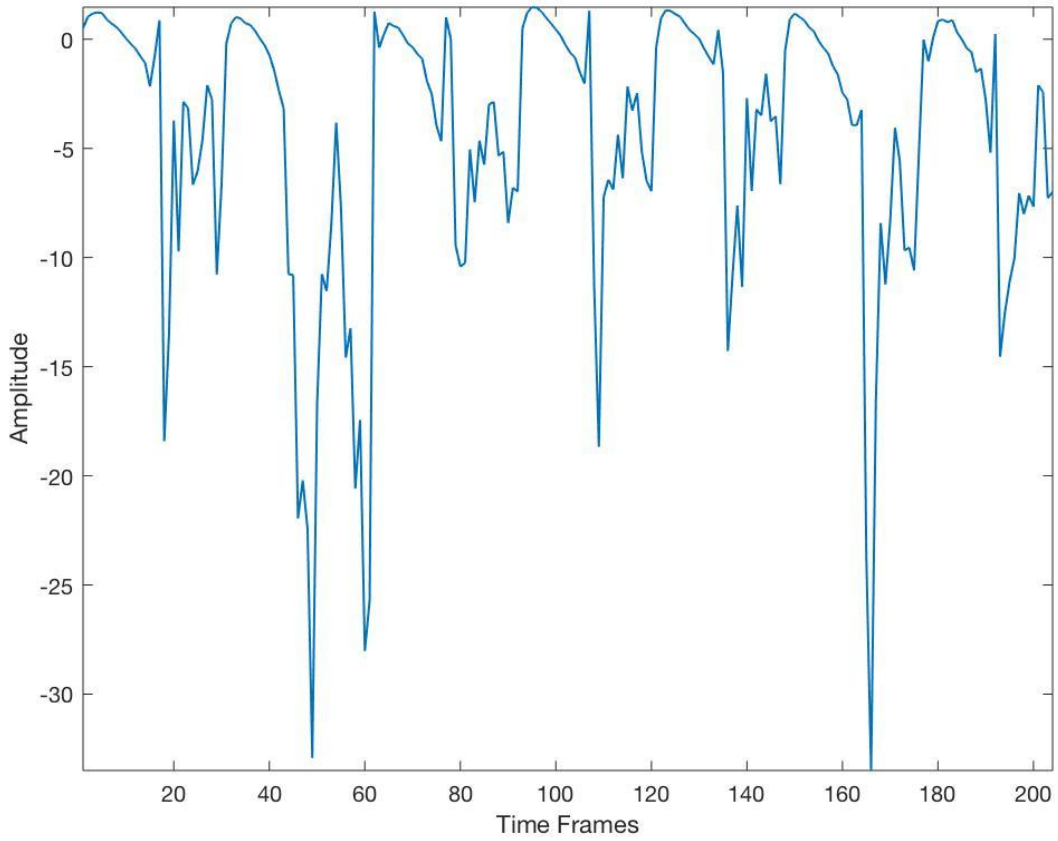


Figure A.2: Logarithm of the hi-hat G values for the test drum beat pattern.

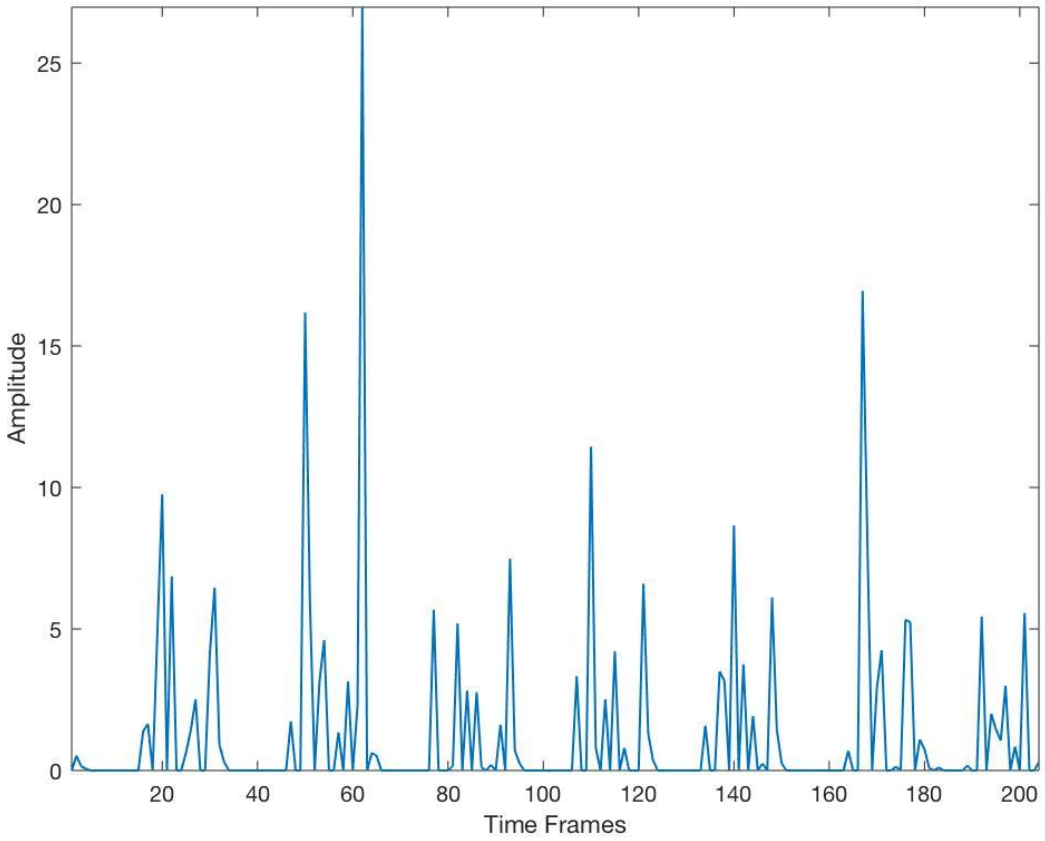


Figure A.3: Half-wave rectified derivative of the logarithm of the hi-hat G values for the test drum beat pattern.

Appendix B: Up-to-Date Classification Results

Table B.1 contains the testing results of the classification algorithm using the most up-to-date microphone placement and thresholding tuning.

Piece(s)	Piece #1	Piece #2	Piece #3	False H	False T	False S	Total
Hi-hat (H)	97	N/A	N/A	0	0	0	97
Snare (S)	100	N/A	N/A	1	0	0	99
Kick (K)	91	N/A	N/A	0	1	0	90
Tom (T)	54	N/A	N/A	0	0	10	45
Crash (C)	87	N/A	N/A	10	0	3	76
H+K	35	94	N/A	1	0	2	33
H+S	29	94	N/A	0	0	0	24
K+S	49	100	N/A	6	3	0	43
C+K	19	94	N/A	11	1	4	14
C+S	6	96	N/A	11	0	1	3
H+K+S	14	71	96	0	0	0	9
C+K+S	0	61	86	8	3	0	0

Table B.1: Up-to-date classification test results.

Each piece or combination of pieces were played 100 times in a row at a tempo of 120 beats per minute. The table details how many times the classification algorithm correctly detected an onset by the piece(s) as well as how many times a false onset was detected, including the false detection of two onsets for one true onset. The number of times that the classification algorithm simultaneously identified all of the pieces that were played without error is recorded in the Total column. Only combinations of pieces that were deemed likely to be played by drummers were tested.

Appendix C: Previous Classification Results

Tables C.1, C.2, and C.3 contain the testing results of the classification algorithm at three different tempos using a different microphone placement and thresholding tuning than those used in Appendix B.

Pieces(s)	Piece #1	Piece #2	Piece #3	False H	False K	False S	Total
Hi-hat (H)	100	N/A	N/A	0	0	0	100
Snare (S)	100	N/A	N/A	0	1	0	99
Kick (K)	56	N/A	N/A	0	8	1	48
H+K	96	55	N/A	0	6	1	46
H+S	28	96	N/A	0	0	0	24
K+S	26	93	N/A	0	0	0	23
H+K+S	56	29	89	1	1	0	13

Table C.1: Previous classification test results at 60 BPM.

Piece(s)	Piece #1	Piece #2	Piece #3	False K	False S	Total
Hi-hat (H)	100	N/A	N/A	0	0	100
Snare (S)	100	N/A	N/A	1	0	99
Kick (K)	68	N/A	N/A	10	0	58
H+K	93	81	N/A	18	3	58
H+S	29	100	N/A	0	0	29
K+S	31	96	N/A	1	0	29
H+K+S	7	18	99	0	0	3

Table C.2: Previous classification test results at 120 BPM.

Piece(s)	Piece #1	Piece #2	Piece #3	False K	False S	Total
Hi-hat (H)	99	N/A	N/A	0	0	99
Snare (S)	99	N/A	N/A	2	0	98
Kick (K)	67	N/A	N/A	0	0	67
H+K	32	57	N/A	0	5	21
H+S	13	100	N/A	0	0	13
K+S	55	86	N/A	0	0	51
H+K+S	18	41	90	0	0	7

Table C.3: Previous classification test results at 235 BPM.

These tests were performed before submitting the poster for Design Expo. At that point, only the kick, snare, and hi-hat were adequately tuned and tested. Each piece or combination of pieces were played 100 times in a row. The table details how many times the classification algorithm correctly detected an onset by the piece(s) as well as how many times a false onsetes was detected, including the false detection of two onsets for one true onset. The number of times that the classification algorithm simultaneously identified all of the pieces that were played without error is recorded in the Total column.

Appendix D: Loading Screen Implementation

When it came to implementing the loading screen, it was first thought to use the index of the loop / length of the loop of the synthesis as a percentage for how far in progress the script was. This removes the amount of time needed to import packages and write the output file itself in the estimation, but takes into account the linear relationship between size of input and length of run time. Therefore, this seemed like an appropriate estimate to use, as when inputs became very large, the time for other processes becomes negligible in comparison.

While obtaining the index of the script while it was running was relatively easy in the Python script itself, getting the C code to know the status of the Python script became difficult. Because both operations were running on the same thread, there had to be some two-way communication method between both scripts. Therefore, reading/writing to a file was out of consideration, as the Python script could not simultaneously be writing to the file while the C code was reading from it.

One idea that was brought up was to "create" files during the Python implementation as progress passed set thresholds. The idea was to essentially create an arbitrary number of set files (say 10) that, when created, meant that some percentage of the synthesis was complete. If there were 10 files, then after the first file was created, the program was at 10% completion, the second file meant 20%, etc. While this method would create an accurate (although considerably discrete) calculation rather than an estimate, the method would require a considerable amount of development. Since the team was on a tight timeline, this method was dropped by utilizing the much simpler method of extrapolating load times based on a line of fit for input beat size.

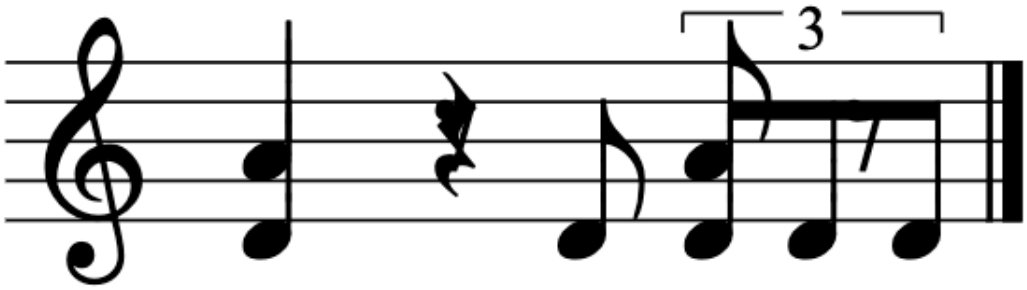
In order to estimate loading times, beats of three different sizes were taken and timed using the Python timer function. After this, a line of best fit was made with the three different beat sizes and then used to extrapolate all future load times. The reason for taking three data points was to remove any outliers from only selecting two data points, without having to construct larger experiments which would have taken more time. It was found that the three points did form a fairly linear fit, and worked pretty well for overall system use. In the average case, the system took longer on busier beats with many components hit and shorter for times when only one component (such as the snare) was hit, but this estimation did not take into account this. Instead, a multiplier of a guess of how many components may be hit was added to the slope of the linear fit, and tested until it "felt right."

While this estimate was actually fairly off of the actual loading time, simply having a loading bar that moved somewhat close to where the program was actually helped users feel like the program

was working with them rather than against them, and that nothing broke during synthesis. While many more accurate methods could have been used to estimate loading progress, the one used was certainly good enough for the purposes of the project.

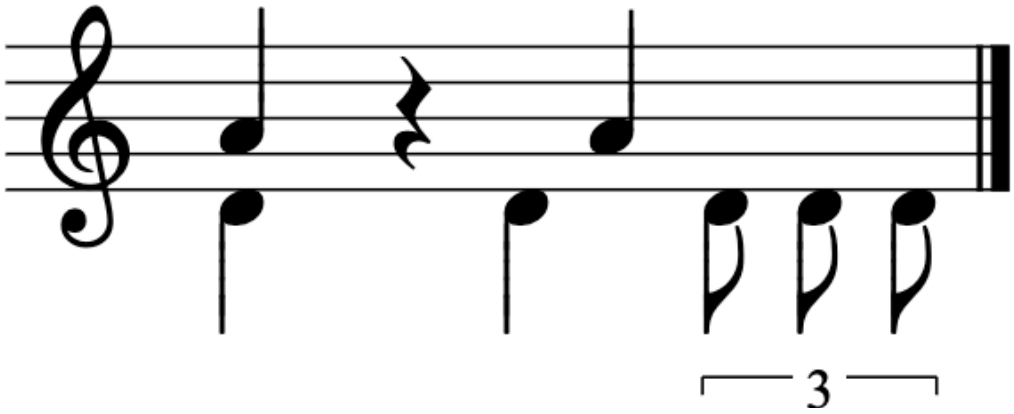
Appendix E: Guido Parsing and Interpretation

An example of pre-processed and post-processed Guido is shown below, to show the types of processing done to make the Guido output look acceptable.



{ [\staff<1> d/4 _/8 d/8 d/12 d/12 d/12], [\staff<1> a/4 _/4 a/8 _/8] }

Figure E.1: Unprocessed Guido that is hard to understand.



{ [\staff<1> \stemsDown d/4 \noteFormat<size=0> d/8 \noteFormat<size=1> d/4 d/12 d/12 d/12], [\staff<1> \stemsUp a/4 \noteFormat<size=0> _/4 \noteFormat<size=1> a/8 \noteFormat<size=0> c/8 \noteFormat<size=1>] }

Figure E.1: Processed Guido that looks visually better.

The GMN generated that for the "unprocessed Guido" is easy to follow, but very difficult to interpret. By removing some of the unnecessary rests, and fixing the direction of the stems, it is far easier to read and understand. The only way to hide these rests is to actually render them as "notes" of arbitrary pitch, and then use \noteFormat<size=0> to set their size to 0, which doesn't render them.

Appendix F: Alternative Transcription Methods

Before fully implementing the absolute spacing method for transcription, one other method was attempted in which a similar comparison computation was performed in the "time" domain. The possible beat patterns were mapped onto a buffer that contained the number of samples per beat, and the similarity between beat patterns and incoming hits were calculated in much the same way. In this case, the computation consisted of a much larger matrix multiplication where the basis matrix contains all possible beat vectors and the input vector contained 0s where no input was classified and 1s where an input was classified. It was found that to make this work accurately, the inputs could not be entered into the input vector simply as a 1 or 0, rather some sort of decay function was necessary to capture the possibility of variation in the input note. Furthermore, it was clear that rests must be given a value of -1 so that where rests lined up a positive value (-1 * -1) was calculated and where hits lined up a positive value (1*1) was detected. Similar to the method detailed above, the same priors were used to modify the amplitude of the hits thus applying the same probability weighting method. This method has two major drawbacks: the computational complexity is significantly increased, and it was far less robust in the prototyping phase. One important criteria for success in the prototyping phase was that a perfect input should imply a perfect output, and this method could never achieve this. This was most likely due to the fact that small changes were amplified as a result of the negative weighting of rests. This method also used far more constant relating to the width of the hit function, the amplitude of the hit, and the same parameters for the basis matrix hits. Finally, this method never provided any advantage over the simple absolute distance comparisons and thus the latter method was chosen as a more robust and simple algorithm.

Appendix G: Hardware Specifics

Specific details regarding the addition of hardware interrupts, timers, and potentiometer readings are given here. These details are primarily added to document difficulties encountered with using the Nucleo documentation. This section should serve as an example of how to implement certain timer interrupt and hardware interrupt functionality should it be relevant in future offerings of the course.

```
25
26 static TIM_HandleTypeDef g_TimHandle3 = {
27         .Instance = TIM5
28 };
29
30 static TIM_HandleTypeDef g_TimHandle = {
31         .Instance = TIM2
32 };
33
34 void TIM2_IRQHandler()
35 {
36     __HAL_TIM_CLEAR_FLAG(&g_TimHandle, TIM_FLAG_UPDATE);
37     HAL_TIM_IRQHandler(&g_TimHandle);
38     HAL_TIM_PeriodElapsedCallback(&g_TimHandle);
39 }
40
```

Figure G.1: Configuration of TIM2 and TIM5 hardware timers (1).

```
void ConfigureTIM()
{
    __TIM2_CLK_ENABLE();
    g_TimHandle.Init.Prescaler = 0;
    g_TimHandle.Init.CounterMode = TIM_COUNTERMODE_UP;
    g_TimHandle.Init.Period = 108000000;
    g_TimHandle.Init.ClockDivision = TIM_CLOCKDIVISION_DIV1;
    g_TimHandle.Init.RepetitionCounter = 0;

    TIM2->EGR = TIM_EGR_UG;
    TIM2->DIER = TIM_DIER_UIE;
    TIM2->CR1 = TIM_CR1_CEN;

    HAL_NVIC_SetPriority(TIM2_IRQn, 15,0);
    HAL_NVIC_EnableIRQ(TIM2_IRQn);

    HAL_TIM_Base_Init(&g_TimHandle);
    HAL_TIM_Base_Start(&g_TimHandle);

    __TIM5_CLK_ENABLE();
    g_TimHandle3.Init.Prescaler = 0;
    g_TimHandle3.Init.CounterMode = TIM_COUNTERMODE_UP;

    g_TimHandle3.Init.Period = 4294967295;
    g_TimHandle3.Init.ClockDivision = TIM_CLOCKDIVISION_DIV1;
    g_TimHandle3.Init.RepetitionCounter = 0;

    TIM5->EGR = TIM_EGR_UG;
    TIM5->DIER = TIM_DIER_UIE;
    TIM5->CR1 = TIM_CR1_CEN;

    HAL_TIM_Base_Init(&g_TimHandle3);
    HAL_TIM_Base_Start(&g_TimHandle3);
}
```

```
void HAL_TIM_PeriodElapsedCallback(TIM_HandleTypeDef *htim)
{
    if (htim->Instance == TIM2 && run_main){
        LED_Green_Toggle();
//      for (int dac_iter = 0; dac_iter < 11017; dac_iter++){

        // Timing:
        //  2000 Iter --> 250 us
        //  4000 Iter --> 500 us

//      while(DAC_Fifo_Put(click[0])==0);
        if (count < 6){
            len = sprintf(packet_buffer, "%s, %i\n", "Count", count);
            SendPacket(SID_TO_WHATEVER, (uint8_t *)packet_buffer, len);
            count++;
        }
        for (int dac_iter = 0; dac_iter < 2000; dac_iter++){
            left = (int16_t)click[dac_iter];
            right = (int16_t)click[dac_iter];

            sample = (((int32_t)left)<<16) | (0x0000FFFF&(uint32_t)right);

            while(DAC_Fifo_Put(sample)==0);
        }

//      TIM2->CNT=0;
//      metronome_count++;
    }
}
```

Figure G.2: Configuration of TIM2 and TIM5 hardware timers (2).

Figures G.1 and G.2 show the settings used to configure two hardware timers. One important note is that only TIM2 and TIM5 hardware timers have 32-bit precision whereas others are lower precision. Only TIM2 was configured as an interrupt timer, hence the definition of TIM2_IRQHandler() in Figure G.1 and HAL_TIM_PeriodElapsedCallback() in Figure G.2. The timer prescaler is a parameter to scale the length of the timer period, the period is in number of clocks times the prescaler value. The ConfigureTIM() function should be called before the main code body is run.

```
void ConfigureADC()
{
    GPIO_InitTypeDef GPIOA_InitStructure;

    __GPIOA_CLK_ENABLE();
    __ADC1_CLK_ENABLE();

    GPIOA_InitStructure.Pin = GPIO_PIN_3;
    GPIOA_InitStructure.Mode = GPIO_MODE_ANALOG;
    GPIOA_InitStructure.Pull = GPIO_NOPULL;
    HAL_GPIO_Init(GPIOA,&GPIOA_InitStructure);

    HAL_NVIC_SetPriority(ADC_IRQn, 0, 0);
    HAL_NVIC_EnableIRQ(ADC_IRQn);

    ADC_ChannelConfTypeDef adcChannel;

    g_AdcHandle.Instance = ADC1;

    g_AdcHandle.Init.ClockPrescaler = ADC_CLOCKPRESCALER_PCLK_DIV2;
    g_AdcHandle.Init.Resolution = ADC_RESOLUTION_12B;
    g_AdcHandle.Init.ScanConvMode = DISABLE;
    g_AdcHandle.Init.ContinuousConvMode = ENABLE;
    g_AdcHandle.Init.DiscontinuousConvMode = DISABLE;
    g_AdcHandle.Init.NbrOfDiscConversion = 0;
    g_AdcHandle.Init.ExternalTrigConvEdge = ADC_EXTERNALTRIGCONVEDGE_NONE;
    g_AdcHandle.Init.ExternalTrigConv = ADC_EXTERNALTRIGCONV_T1_CC1;
    g_AdcHandle.Init.DataAlign = ADC_DATAALIGN_RIGHT;
    g_AdcHandle.Init.NbrOfConversion = 1;
    g_AdcHandle.Init.DMAContinuousRequests = ENABLE;
    g_AdcHandle.Init.EOCSelection = ADC_EOC_SEQ_CONV;

    HAL_ADC_Init(&g_AdcHandle);

    adcChannel.Channel = ADC_CHANNEL_3;
    adcChannel.Rank = 1;
    adcChannel.SamplingTime = ADC_SAMPLETIME_480CYCLES;
    adcChannel.Offset = 0;

    if (HAL_ADC_ConfigChannel(&g_AdcHandle, &adcChannel) != HAL_OK)
    {
        asm("bkpt 255");
    }

}
```

```
if (HAL_ADC_PollForConversion(&g_AdcHandle, 1000000) == HAL_OK)
{
    adc_val = HAL_ADC_GetValue(&g_AdcHandle);

    if (abs(adc_val - prev_adc_val) > 75)
    {
        BPM = 60 + (adc_val*(180.0/4095));
        cycles_per_period = 108000000.0 * (60.0/BPM);
        len = sprintf(packet_buffer, "BPM, %i \n", BPM);
        SendPacket(SID_TO_WHATEVER, (uint8_t *)packet_buffer, len);
        TIM2->ARR = cycles_per_period;
        prev_adc_val = adc_val;
    }
```

Figure G.3: ADC configuration for use with potentiometer.

Figure G.3 shows an example of configuration settings for the Nucleo ADC to be used with an analog GPIO pin. The top graphic shows the necessary configuration call that should be done before the main body of code is run, and the bottom graphic shows the method for reading the value from the ADC during runtime.

```
void EXTI9_5_IRQHandler(void)
{
    time_diff = TIM5->CNT;
    TIM5->CNT = 0;

    if((__HAL_GPIO_EXTI_GET_IT(GPIO_PIN_9) != RESET) && !run_main)
        {
            __HAL_GPIO_EXTI_CLEAR_IT(GPIO_PIN_9);
            if (!run_main && time_diff > 30000000){
                len = sprintf(packet_buffer, "%s\n", "Playback");
                SendPacket(SID_TO_WHATEVER, (uint8_t *)packet_buffer, len);
            }
        }
}
```

```
__GPIOC_CLK_ENABLE();
GPIOC_InitStructure.Pin = GPIO_PIN_12 | GPIO_PIN_9;
GPIOC_InitStructure.Mode = GPIO_MODE_IT_RISING;
GPIOC_InitStructure.Speed = GPIO_SPEED_HIGH;
GPIOC_InitStructure.Pull = GPIO_PULLDOWN;
HAL_GPIO_Init(GPIOC, &GPIOC_InitStructure);
```

Figure G.4: GPIO interrupt configuration.

Figure G.4 shows the settings to configure a hardware interrupt pin. Only the interrupt call for GPIO_PIN_9 is shown as EXTI9_5_IRQHandler is used only for pins 5 to 9. An additional call was made to EXTI15_10_IRQHandler for GPIO_PIN_12.

```
static void SystemClock_Config(void)
{
    RCC_ClkInitTypeDef RCC_ClkInitStruct;
    RCC_OscInitTypeDef RCC_OscInitStruct;

    __HAL_RCC_PWR_CLK_ENABLE();
    __HAL_PWR_VOLTAGESCALING_CONFIG(PWR_REGULATOR_VOLTAGE_SCALE2);

    RCC_OscInitStruct.OscillatorType = RCC_OSCILLATORTYPE_HSE;
    RCC_OscInitStruct.HSEState = RCC_HSE_ON;
    RCC_OscInitStruct.PLL.PLLState = RCC_PLL_ON;
    RCC_OscInitStruct.PLL.PLLSource = RCC_PLLSOURCE_HSE;
    RCC_OscInitStruct.PLL.PLLM = 8;
    RCC_OscInitStruct.PLL.PLLN = 288;
    RCC_OscInitStruct.PLL.PLLP = RCC_PLLP_DIV2;
    RCC_OscInitStruct.PLL.PLLQ = 6;
    HAL_RCC_OscConfig(&RCC_OscInitStruct);

    RCC_ClkInitStruct.ClockType = (RCC_CLOCKTYPE_SYSCLK | RCC_CLOCKTYPE_HCLK | RCC_CLOCKTYPE_PCLK1 | RCC_CLOCKTYPE_PCLK2);
    RCC_ClkInitStruct.SYSCLKSource = RCC_SYSCLKSOURCE_PLLCLK;
    RCC_ClkInitStruct.AHBCLKDivider = RCC_SYSCLK_DIV1;
    RCC_ClkInitStruct.APB1CLKDivider = RCC_HCLK_DIV4;
    RCC_ClkInitStruct.APB2CLKDivider = RCC_HCLK_DIV2;
    HAL_RCC_ClockConfig(&RCC_ClkInitStruct, FLASH_LATENCY_4);
    SystemCoreClockUpdate();

    if (HAL_GetREVID() == 0x1001)
        __HAL_FLASH_PREFETCH_BUFFER_ENABLE();
}
```

Figure G.5: System clock settings.

Figure G.5 shows the clock settings as they were configured for use with the ADC and TIM2/5 hardware interrupts.