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Synchronizing Sequencing Software to a Live Drummer

Abstract: This article presents a method of adjusting the tempo of a music software sequencer so that it remains synchronized with a drummer's musical pulse. This allows music sequencer technology to be integrated into a band scenario without the compromise of using click tracks or triggering loops with a fixed tempo. Our design implements real-time mechanisms for both underlying tempo and phase adjustment using adaptable parameters that control its behavior. The aim is to create a system that responds to timing variations in the drummer's playing but is also stable during passages of syncopation and fills. We present an evaluation of the system using a stochastic drum machine that incorporates a level of noise in the underlying tempo and phase of the beat. We measure synchronization error between the output of the system and the underlying pulse of the drum machine and contrast this with other real-time beat trackers. The software, B-Keeper, has been released as a Max for Live device, available online at www.b-keeper.org.

Introduction and Motivation

One challenge currently faced by rock and pop bands is how to incorporate electronic and pre-recorded musical parts when playing live. In the studio, bands typically use multi-track tape and Digital Audio Workstation (DAW) software to overdub extra parts and combine these together in an offline editing process. In the digital sequencer, audio effects, panning, and volume changes can all be automated when crafting the mix of a song, with the result that listeners are increasingly used to hearing an idealized and transformed representation of sound. These processes contribute to making such performances difficult to recreate live. As a result, bands often make use of pre-recorded audio, either through triggering samples or by playing along to backing tracks.

The problem with this is that the pre-recorded material does not respond to timing fluctuations of the band in the way that musicians do, so that often the musicians are forced to follow the timing dictated by the backing track via a click track. In the studio, there has been an increasing prevalence for the use of click tracks on recordings (Lamere 2009). Often bands record digitally onto DAW software, also referred to as sequencers, which control the playback of audio tracks and MIDI messages. Commercial sequencers include Ableton Live, Pro Tools, Logic Studio, Nuendo, and others. These programs provide an optional click track when recording, thereby providing audible feedback to the drummer and other musicians when recording to ensure that they stay "in time." This means the resulting performance has very accurate timing. When a fixed tempo is used, it simplifies the offline editing procedure, because when sections of audio are moved between different locations of the song they are still at the correct tempo. It also allows timing "quantization," whereby the timing of events is corrected to align more closely with the underlying grid.

Although in the studio these restrictions may also have some advantages, in live performance the backing track restricts the freedom of musicians to make changes in timing and isolates the drummer through the required wearing of headphones. In the situation where musicians want technology to be incorporated into their live shows, there is a need for an accurate synchronization system that keeps the sequencer in time with the band rather than forcing the musicians to play to a click track. In this article, we present an algorithm to control the tempo of sequencer, thereby allowing recorded parts or backing tracks to respond to subtle changes in tempo in the way that musicians would naturally respond when playing together.

We first present relevant background material to explain our design methodology. In the subsequent section, we explain our design of the algorithm and then describe two approaches to evaluating the

Computer Music Journal, 37:2, pp. 46–60, Summer 2013
doi:10.1162/COMJ_a_00178

system. In order to successfully track the timing variations of a drummer, we first need to look at the nature of drum signals and how drummers behave.

Drumming, Rhythm, and Beat Tracking

In popular music, performers generally take their cue from the drummer and it therefore makes sense to align the sequencer as accurately as possible to the drum beat.

Rhythmic Features of Drumming

In rock and pop music, an interlocking pattern is created by the kick drum (also called the bass drum), the snare drum, and the cymbal pattern, played on the hi-hat or ride. Jeff Pressing (2002) characterizes the qualities associated with what he terms "Black Atlantic Rhythm," the rhythms shared culturally between America and Africa, which have given rise to most forms of popular music: blues, jazz, rock, reggae, hip-hop, etc. The devices used by these rhythms all rely on the "support of a firmly structured temporal matrix," defined as a "groove," characterized by the perception of a regular pulse with a subdivision structure and of a longer repeating time cycle. Rhythmic devices enumerated by Pressing that "build on the groove" include syncopation, displacement, off-beat phrasing, polyrhythm, hocketing (an interlocking pattern shared between multiple instruments), and swing. There is a conflict between a fixed pulse and various timing accents played against it (Waadeland 2001), and individual drum events can display microtime deviation from the regular beat that defines the groove (Iyer 1998; Freeman and Lacey 2002). Meter can then be defined as the hierarchical structure emerging from the occurrence of alternating strong and weak beats as proposed in *The General Theory of Tonal Music* (GTTM; cf. Lerdahl and Jackendorff 1983). Drum patterns are built around a regular metric structure. Klapuri, Eronen, and Astola (2006) identify the *tactus* or beat level as the regular pulse at which trained humans tap in time with music.

Music Perception of Musical Beats and Rhythm

To successfully follow a beat, we need to solve two problems: updating the underlying tempo, and making phase updates so that we remain precisely aligned (Gouyon and Dixon 2005). There are indications from music psychology that humans solve these problems separately. The two-level timing model, first suggested by Wing and Kristofferson (1973), also found in Mates (1994) and in Vorberg and Wing (1996), posits separate mechanisms for period (i.e., tempo) and phase, leading to the implication that changes in phase can be made independently of changes in period. Repp (2005) proposed a similar two-process model to explain how humans tap in time, featuring a fast phase-synchronization process and a slower process that measures the underlying tempo.

Automatic Beat Tracking

Computer-based beat trackers aim to accept a musical signal as input and to produce as output a pulse at intervals where humans would naturally tap "in time" to the music (Hainsworth 2006). Beat trackers tend fall into two categories: event-based and audio-based. Event-based beat-tracking algorithms process symbolic input, such as a list of discrete onset times generated by an onset detector. Audio-based beat trackers process features derived from the audio signal, such as an onset detection function's output that represents the degree to which the corresponding audio frame contains the onset of a new musical event.

Event-based multiple-agent approaches were used by Dixon (2007) and Goto and Muraoka (1996), the latter exploiting the regular kick- and snare-drum pattern found in pop and rock music. McAuley (1995), Large (1995), Large and Kolen (1994), Toiviainen (1998), and Eck (2002) have investigated the use of adaptive oscillators for symbolic beat tracking, whereby the oscillators adjust their tempo and phase only when observing onsets at certain points during their cycle. For audio-based analysis, Bello et al. (2005) describe methods for the generation of the onset detection

function, which include changes in energy and spectral change. Audio-based approaches to beat tracking often make use of comb filtering (Scheirer 1998) and autocorrelation (Eck 2007; Davies and Plumbley 2007; Stark, Davies, and Plumbley 2008) to subsequently process the output of the onset detection function.

One major difficulty for the live beat-tracking problem is that many previous algorithms for beat tracking have been designed to analyze audio files offline, such as for the Music Information Retrieval eXchange (MIREX) annual competition. As a result, many algorithms addressing this task are designed to be as flexible as possible, giving the highest average performance on a wide variety of songs. They cannot be depended on to always track the beats correctly in any given musical signal, however. Common errors are switching to tapping on the off-beat, difficulties in following complex rhythmic sequences such as syncopation, and shifting to a wrong but related tempo (Dannenberg 2005).

Design of the Drum-Tracking Algorithm

We want to design a robust algorithm for tracking drums that will always remain in time for most rock and pop music. Because traditional beat-tracking algorithms experience difficulties at correctly tracking some types of signals, we shall make three reasonable assumptions according to the kind of situation where we envisage the algorithm will be used. This will enable us to simplify the problem and to design a robust beat-tracker for this kind of situation.

1. Event-based input: To use accurate onset timing information as input to our beat tracker, we should take advantage of the fact that the input to the system is a drum signal. Dedicated microphones (usually dynamic, using electromagnetic induction) are often placed on each drum in both the studio and live environments. This microphone arrangement means that we have a reasonable separation, both acoustically and physically, between the kick drum and snare, although there may be some "bleed" between them. In rock and pop music, these signals tend to have fast transients and high sound pressure created by drum events. Onset detection can then provide event times for the kick and snare drum. Real-time onset detectors include the `bonk~` object for Max/MSP by Puckette, Apel, and Zicarelli (1998) and the C++ *aubio* library by Brossier, Bello, and Plumbley (2004).
2. Initial tempo estimate: We will assume that an initial tempo estimate is available, e.g., by tapping the drum sticks as a "count-in," a well-known technique often used by musicians in performance.
3. Known meter: To know the position of each event within the bar, we will assume a constant known metrical rhythm, such as 4/4. Where this changes, an operator might inform the algorithm by intervention, for instance by sending a message in the software, or the message could be automatically sequenced. This allows us to place more emphasis on events that have more significance in the metrical hierarchy.

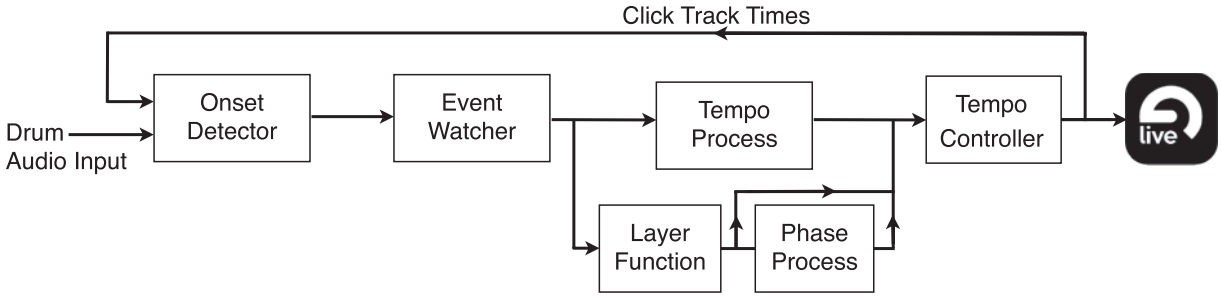
The output of the algorithm controls the tempo of a sequencer in order to synchronize the musical events with a live performance. A click track sent from the sequencer is used to communicate its beat position. For the beat tracker, we follow the two-process model, similar to that of Repp (2005), consisting of a tempo process that updates the underlying tempo, and a phase-synchronization process that aims to align the beat locations of the sequencer with the drum onsets that occur on a beat. In our implementation we make use of the sequencer Ableton Live.

An overview of the algorithm is shown in Figure 1. We will now describe in more detail the design of the two components for tempo and phase synchronization.

Phase Synchronization Process

We have seen from experiments in music psychology that humans tapping to an isochronous pulse

Figure 1. Overview of the algorithm with components for tempo and phase update.



will quickly respond to minimize the timing discrepancy between their taps and the pulse (Repp 2005). The onset event list may also include musically expressive events and off-beat events from syncopated rhythms, however. From the observation that human tappers tend to synchronize with the *main beats* in the bar (Klapuri, Eronen, and Astola 2006), we prioritize synchronization to drum events at the metrical level of the beat. In a regular meter, these would consist of the "one," "two," "three," and "four" as opposed to the eighth notes between them (the "and"s). The snare drum can exhibit complex rhythms and expressive timing relative to the kick drum (Iyer 1998; Freeman and Lacey 2002), and thus we choose to prioritize synchronization to the latter over the snare. These two preferences can be considered as two "rules" that guide our design of the synchronization process. In order to implement these rules, we will quantify certain attributes of events such as the accuracy of the beat (relative to the sequencer's position given by an internal click track) or the importance of a particular metrical location.

The system uses the click track of the audio sequencer to provide an approximation of the current beat location. Whereas other beat-tracking algorithms infer the beat position directly from the audio signal, we assume that the click track is close to that of the underlying beat from the drums. This allows us to interpret events relative to their position in the bar and removes the necessity for an additional stage for phase correction. Often, the sequencer is playing musical parts, and thus there is audible feedback confirming that the representation of the beat position used by the system is correct.

We make use of an accuracy function that quantifies how close the new onset at time t_n is to the predicted beat time provided by the click track at time $E[t_n]$ by using a non-normalized Gaussian window around the predicted time:

$$a(t_n) = g(t_n - E[t_n], \sigma_{sync}) \tag{1}$$

where g is the non-normalized Gaussian function:

$$g(t, \sigma) = \exp\left(-\frac{t^2}{2\sigma^2}\right) \tag{2}$$

The width of the Gaussian window is parameterized by σ_{sync}, the standard deviation, which reflects our current uncertainty about the beat position. When σ_{sync} is large, the Gaussian window is wider, and so the value of the accuracy function remains high for larger time differences between the observed onset and the expected beat location. This results in more response to timing variation. When the Gaussian window's standard deviation is smaller, the accuracy function is focused around the expected beat and we are more likely to ignore events that are not close to the metrical divisions of the bar.

We rate the metrical importance of incoming events by quantizing to the closest eighth note. We use a weighting measure, $L_{sync}(k)$, which gives preference to events on the main beats. We set

$$L_{sync}(k) = \begin{cases} 1 & \text{if } k \text{ is even} \\ l_{odd} & \text{if } k \text{ is odd} \end{cases} \tag{3}$$

where k is the quantized metrical position of the beat in eighth notes from the beginning of the bar, and

l_{odd} is the weight given to the eighth notes between the main beats. We used the value $l_{odd} = 0.4$ so that events on the beat are given more weight and are therefore more likely to be used for synchronization.

To prioritize the main beats of the bar for synchronization, we use an update rule that states:

> IF a drum onset event is accurate AND on a metrically important beat,
> THEN synchronize to that event.

To implement this rule, we have derived two measures from the timing data: accuracy of the drum event relative to the current beat estimate given in Equation 1, and metrical importance given in Equation 3. We combine these using the algebraic product (multiplication) into a single measure between zero and one that quantifies the extent to which an event is both accurate and on a metrically important beat. Our combined function, reflecting our belief that the event is accurately timed and on a metrically important beat, is

$$f(t_n) = a(t_n)L_{sync}(p_n) \tag{4}$$

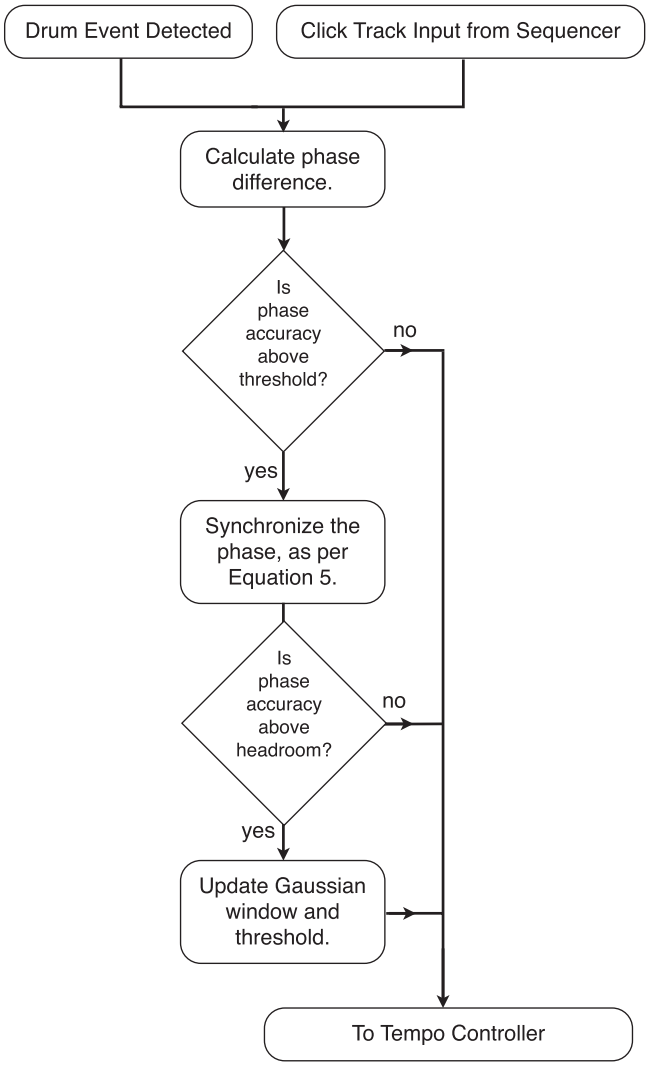
where p_n is the quantized bar position of the onset at time t_n in eighth notes.

The decision about whether an event requires synchronization is made by evaluating the combined function relative to a threshold. Thus, if $f(t_n) > \theta_{sync}$, the current threshold, then we synchronize to this event. We introduce a control parameter $0 \leq \beta \leq 1$ that determines the extent to which the system will make a corresponding phase adjustment for observations above the threshold but away from the expected beat location. Then our synchronization adjustment is:

$$\Delta T_{sync} = \left(\frac{f(t_n) + \beta}{1 + \beta} \right) L_{sync}(p_n)(t_n - E[t_n]) \tag{5}$$

By setting β close to its maximum value of one, the value of the fractional term is increased for any given value of $f(t_n)$ less than one, thereby tending towards full phase synchronization for all observations over the threshold. The design for the phase synchronization component of the algorithm is shown in Figure 2.

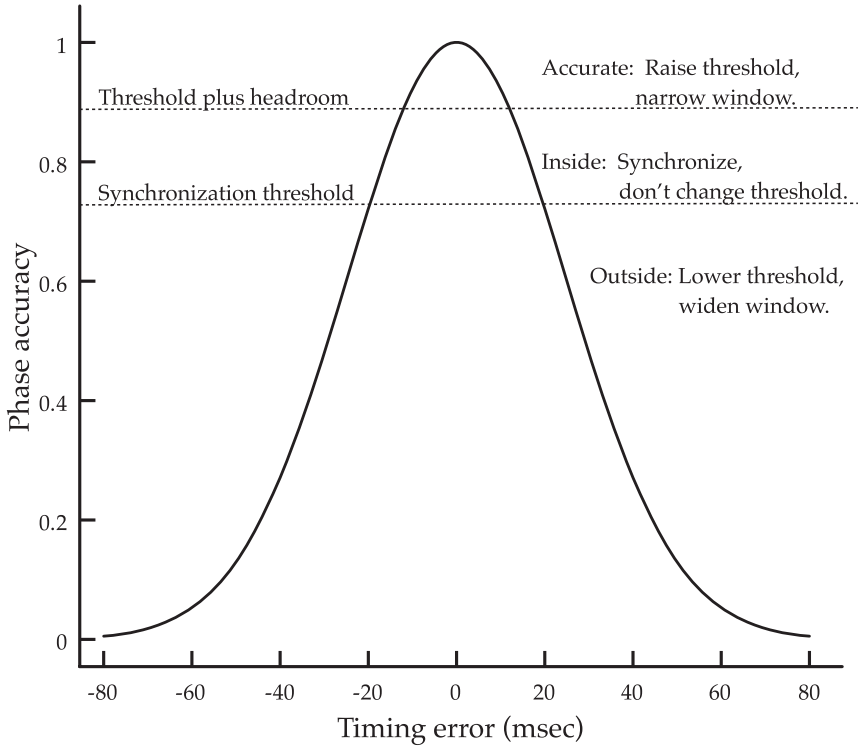
Figure 2. Overview of the phase synchronization component of the algorithm.



Automatic Adjustment of Control Parameters

In early versions of the system, where we used static windows around the beat locations (Robertson and Plumbley 2007), we found that it was difficult to achieve the right balance of responsiveness and reliability in the drum tracker. Syncopated rhythms, drum fills, and passages featuring complex rhythmic information commonly present difficulties for beat trackers (Dannenberg 2005). We experienced similar problems when the threshold and window

Figure 3. Illustration of the different regions for decisions taken by the synchronization algorithm for a standard deviation of 30 msec. The zones that cause adjustment are labeled "Accurate" and "Outside."



parameters were set by hand. Events such as sixteenth notes or eighth-note triplets could be mistaken for the main quarter notes, which denote the beat, thereby causing an erroneous synchronization. Ideally, we would like the receptive window around the beat locations to be as narrow as possible so that these other syncopated events will happen outside and be ignored. We also want the tracker to be responsive to events that do fall on the beat, however, and so we require the window to be wide enough that these are correctly identified.

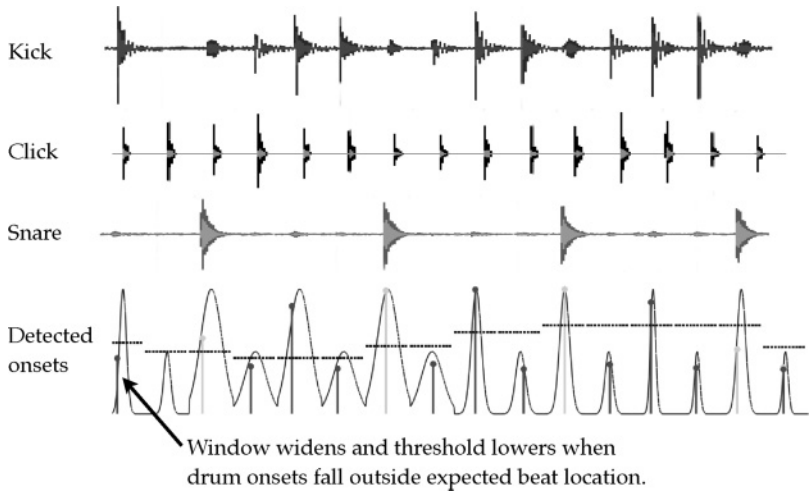
To find a balance between these criteria, we automatically adjust the threshold and the standard deviation of the Gaussian window. As illustrated in Figure 3, there are three zones into which the beat can fall, two of which cause alteration to these control parameters. When the accuracy is above $\theta_{sync} + h$, where h is an extra amount of "headroom," the threshold is raised and the window narrowed. Similarly, when the accuracy is below the threshold, we decrease the threshold and widen the window. For details of how this adjustment is performed see Robertson (2009).

The drum tracker continually adapts its behavior to achieve a balance between being responsive to subtle timing shifts and ensuring the reliability of the system in handling complex rhythms and fills. This can be seen in Figure 4, where the first kick-drum onset has a combined accuracy measure that is beneath the threshold. There is an automatic adjustment of the width of the Gaussian windows around the subsequent expected beat locations to maintain synchronization.

Layer Function

Interpretation of rhythm takes place through a "layer function," which labels the onsets according to their metrical position and restricts the automatic adjustment to occur only upon the main beat events. If a recent onset has higher metrical position,

Figure 4. Illustration of the synchronization process responding to kick and snare events.



according to the GTTM hierarchy (Lerdahl and Jackendorff 1983), and it was accurate, then neither widening nor adjustment of the threshold for events of a lesser metrical position will take place. Where the rhythm is syncopated, or during drum fills where there is rapid playing on subdivisions of the beat, the layer function maintains the same system parameters. These parameters are sufficient to correctly identify and synchronize with the main beats.

We have seen in the section on "Rhythmic Features of Drumming" how drum beats are built around the structure of the groove, with individual hits exhibiting microtime delay that characterizes the "feel" of what is being played. When encountering expressive timing and swing, the layer function will prioritize the main downbeat. Phase synchronization will only take place on the lesser metrical level of "two" and "four" if the onset event is more accurate with respect to the sequencer's click track. Phase synchronization parameters are still automatically adapted for main drum events that have lower accuracy than the threshold, in order to maintain the responsiveness of the drum tracker.

Tempo Process

To make the system robust for live performance, we seek to make the smallest possible change to the tempo that agrees with the observed timing data. To do so, we look at all recent inter-onset intervals (IOIs) between the new onset event at time t_n and any recent event within the last two measures (or 16 eighth notes). Out of the IOIs corresponding to musically regular durations (such as an eighth note, quarter note, half note, or whole note), we find that which most closely matches the current tempo. We adapt the tempo estimate if these two values are sufficiently close. We embody this heuristic in the following rule:

> IF the closest IOI matches the current tempo
> AND is of regular duration
> THEN adapt the tempo towards the beat period
> suggested by the IOI.

The IOI between the new event and another recent event at time t_k has duration $t_k - t_n$. Then the closest corresponding integer multiple of eighth note durations at the current tempo is

$$\nu_{n,k} = round\left(\frac{t_n - t_k}{\tau}\right) \tag{6}$$

where τ is the duration of an eighth note at the current tempo and round(x) gives the closest integer to x. Then the error between the observed interval and that predicted by the current tempo estimate is

$$\varepsilon_{n,k} = (t_n - t_k) - \nu_{n,k}\tau \tag{7}$$

We quantify how well this accords to the current tempo estimate by using a Gaussian function that is also weighted to favor regular intervals. Our combined weighting for the interval between current onset n at time t_n and previous onset k at time t_k is

$$m(n,k) = g(\varepsilon_{n,k}, \sigma_{tempo})\, W(\nu_{n,k}) \tag{8}$$

where $g(\varepsilon_{n,k}, \sigma_{tempo})$ is the non-normalized Gaussian function defined in Equation 2, and $W(\nu_{n,k})$ are the interval weights. To favor only intervals that correspond to the eighth note, quarter note, half note, and whole note durations, which we expect to observe in a regular drum pattern, we used heuristically determined values of $W(1) = 0.9$, $W(2) = 1$, $W(4) = 1$, $W(8) = 0.8$, and $W(16) = 0.8$, and we set $W(k)$ to zero for other k. We evaluate this measure for all intervals between the new event and events that have happened in the most recent two bars. The winning measure is the interval, between the current onset and the "best" onset k^*, that exhibits the best combination of agreeing with the current tempo hypothesis and corresponding to these preferred durations. Then

$$k^* = \arg\max_k m(n,k) \tag{9}$$

where k^* is the index of the onset time with the highest weighting. We decide whether to use the winning interval to update the underlying tempo by evaluating the highest measure relative to a threshold. If $m(n,k^*) > \theta_{tempo}$, then the tempo is updated, so that we assign

$$\tau \leftarrow \tau + \alpha m(n,k^*) \frac{\varepsilon_{n,k^*}}{\nu_{n,k^*}} \tag{10}$$

As in the case of the synchronization process, we dynamically adjust the threshold, θ_{tempo}, and standard deviation, σ_{tempo}. So, if $m(n,k^*) < \theta_{tempo}$, the threshold θ_{tempo} is decreased and σ_{tempo}, in Equation 8, is increased, and vice versa if $m(n,k^*) > \theta_{tempo}$.

Implementation

The algorithm has been coded as a Java external within Max/MSP (Puckette 2002). The onset times for kick and snare events are provided by the `bonk~` onset detector object (Puckette, Apel, and Zicarelli 1998) for percussive signals. For real-time adjustment of the tempo, we have used the audio sequencer Ableton Live 9, which uses zplane's "élastique" algorithm for time stretching (www.zplane.de). In order to avoid latency problems due to soundcard buffering and the onset detection process, we send the audio click track that communicates the beat position of the sequencer through the same process as the drum signals by sending it out and back in through the soundcard, then through the onset detector.

System Evaluation

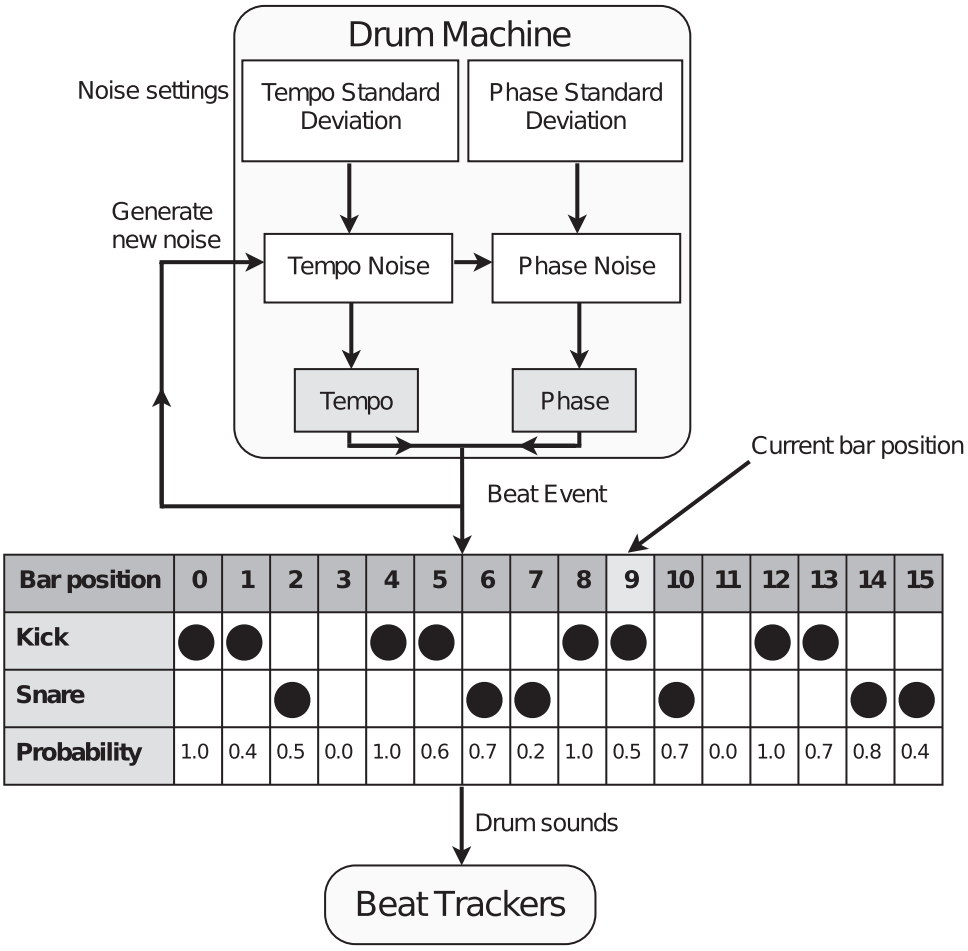
Traditionally, offline beat-tracking algorithms are tested against a database of songs from many genres. There is no database that can be used for such a specialized drum tracker, however. In earlier work (Robertson, Bryan-Kinns, and Plumbley 2008; Stowell et al. 2009) we performed an interactive evaluation of a version of B-Keeper using a "musical Turing test" with human drummers. We concluded that B-Keeper is perceived as behaving closer to a human tapper than to a steady state (e.g., a metronome).

To perform an automatic evaluation, allowing us to assess the range of timing variability that can be accommodated by the system, we constructed a "Stochastic Drum Machine" and performed a comparative evaluation with other real-time beat-tracking systems.

Evaluation with a Stochastic Drum Machine

The Stochastic Drum Machine simulates a simple drummer. It exhibits controllable randomness in the pattern that it plays and incorporates a level of variability ("noise") in the underlying tempo and phase of the beat. Using this, we can quantify the error between the underlying beat and the predicted beats of a beat-tracking algorithm under test. For each "noise" setting, the drum machine is initialized at 120 beats per minute (BPM), typically

Figure 5. Design for the stochastic drum machine. For each eighth note of the bar, there is a possible event type and associated probability that this event will play.



Bar position	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Kick	●	●			●	●			●	●			●	●		
Snare			●				●	●			●				●	●
Probability	1.0	0.4	0.5	0.0	1.0	0.6	0.7	0.2	1.0	0.5	0.7	0.0	1.0	0.7	0.8	0.4

used in the DAW Logic Pro and the preferred tempo of the beat-tracking system designed by Davies and Plumbley (2007). The drum machine proceeds in eighth-note steps. On any given step, rather than a pre-determined pattern, there is a probability that a kick or snare event will play. These patterns of possible kick and snare events and their associated probabilities, are shown in Figure 5. These were set heuristically so that it plays a regular rhythm with occasional syncopated events at the eighth note level.

At every quarter note, Gaussian noise of zero mean and a set standard deviation is added to both the beat period and to the phase offset, the latter corresponding to a local tempo shift in the terminology of Gouyon and Dixon (2005). The standard deviation of the underlying "tempo noise" was varied between 0 and 16 msec per quarter note (where 16 msec is approximately 3.2 percent of the beat period), and the standard deviation of the "phase-offset noise" varied between 0 and 64 msec, added at every eighth note.

Evaluation Results

We first looked at a qualitative evaluation of three different beat trackers: our proposed B-Keeper; the `btrack~` external object for Max/MSP developed by Stark, Davies, and Plumbley (2009); and

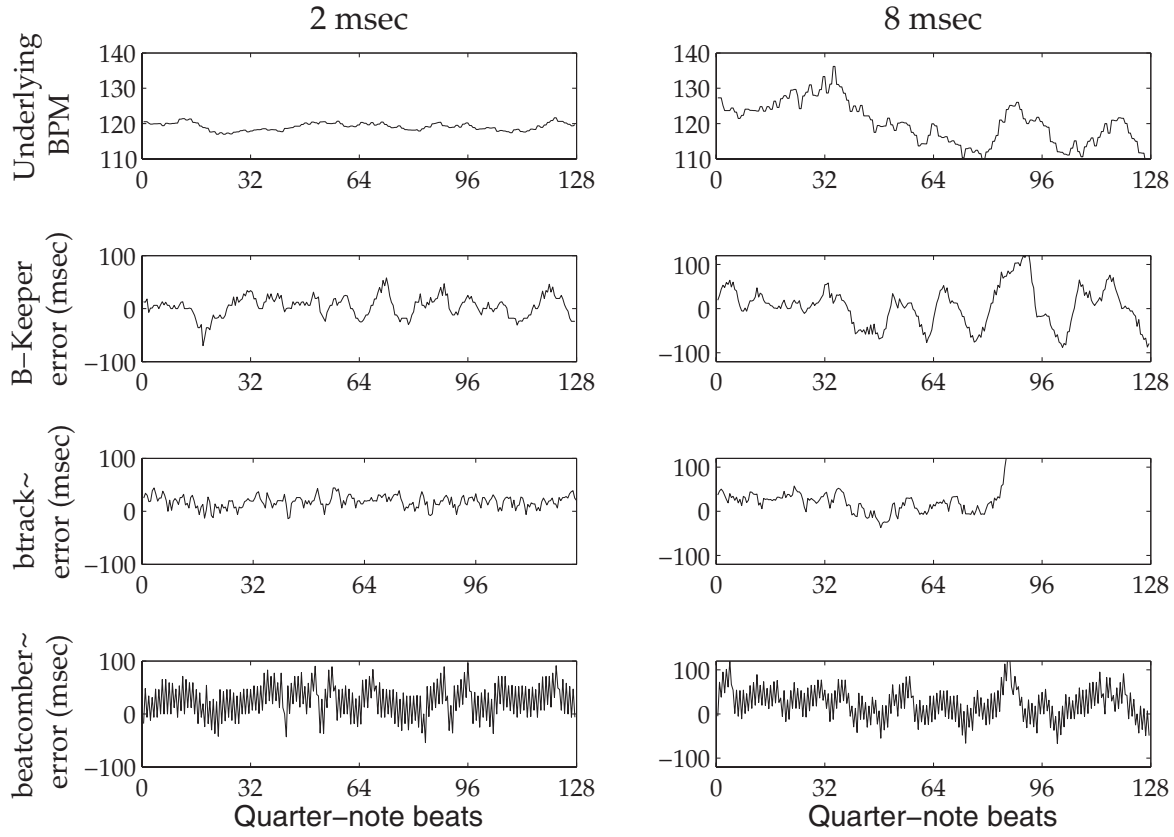


Figure 6. Diagram of the BPM plots (top) and the three beat trackers' errors (in msec) at two different values of standard deviation for Gaussian noise introduced into the underlying beat period: 2 msec per quarter note (left) and 8 msec per quarter note (right). The phase-offset noise has a standard deviation of 8 msec per eighth note in both.

`beatcomber~`, an external object that uses a comb filter matrix, developed by Robertson, Stark, and Plumbley (2011), and which resembles the approach of Eck (2007). The larger values in either process (adding tempo noise or phase-offset noise) resulted in rather "unmusical" drum patterns where the rhythm sounds jerky and unpleasant. We conducted an informal analysis of ten recordings by The Beatles which featured a strong drum component using a method to find the optimal phase and tempo variations for a set of beat annotations (Robertson 2012). These had mean standard deviations between 2.3 and 4.5 msec for the tempo variations and 5.5 and 9.1 msec for the phase variations, suggesting that the bounds of noise we are testing would approximate those present in the steady sections of real-world recordings.

Figure 6 shows the tempo output for standard deviations of 2 msec and 8 msec. In the left-hand plots, we can observe how all beat-trackers respond successfully to the lesser degree of noise. The higher degree of noise, however, gives rise to sudden variations in tempo, which can be problematic. In this case it has caused the `btrack~` algorithm to skip a beat and misalign.

We then quantitatively measured and compared the beat times that the three different beat trackers produced as output. We ran the experiment a total of 25 times for each possible combination of noise settings. Each trial had a duration of 32 bars, or 128 beats. The performance error between the beat times for the drum machine and the predicted beat times for each beat tracker were measured as the standard deviation in both Gaussian noise processes was increased. The other two beat trackers, `btrack~` and `beatcomber~`, do not have the same latency compensation as B-Keeper, so we corrected for latency in those two cases by passing the output of the drum machine through an onset detector that has

Table 1. Median Error for Beat Trackers Synchronizing to Stochastic Drum Machine

Tempo noise	*Phase noise*															
	0		*4*		*8*		*12*		*16*		*20*		*24*		*28*	
0.0	**4** 27	16	**7** 26	14	**9** 26	13	**13** 26	**13**	16 26	**13**	20 26	**17**	25 26	**19**	26 27	**20**
0.5	**7** 26	14	**7** 26	15	**10** 25	14	**13** 25	**13**	18 25	**15**	30 26	**17**	31 26	**19**	27 28	**21**
1.0	**8** 25	12	**8** 25	12	**11** 24	13	**14** 24	15	18 25	**16**	23 26	**19**	26 27	**19**	42 27	**21**
1.5	**8** 24	13	**9** 24	12	**11** 24	13	**15** 24	**15**	18 25	**16**	23 25	**18**	48 27	**19**	30 27	**20**
2.0	**9** 25	13	**10** 25	13	**12** 25	14	**16** 25	**16**	20 25	**17**	24 25	**19**	29 26	**20**	51 28	**22**
2.5	**10** 25	14	**11** 24	13	**13** 25	14	17 25	**15**	22 25	**18**	25 26	**19**	26 27	**20**	34 28	**23**
3.0	**11** 25	14	**13** 25	15	**14** 24	15	18 25	**16**	22 25	**17**	26 26	**19**	32 26	**20**	44 29	**23**
3.5	**13** 24	15	**13** 25	13	**15** 25	**15**	19 25	**15**	21 25	**17**	28 25	**19**	40 27	**21**	47 27	**23**
4.0	14 24	**13**	16 25	**14**	16 25	**14**	21 25	**16**	23 25	**18**	30 26	**20**	52 27	**22**	56 27	**21**

Median error between the beat output times of the stochastic machine and the beat trackers at the lower levels of noise, specified by the standard deviation for the Gaussian noise added (in msec). The median error times for different controllers are all shown: B-Keeper in the top-center of each cell, BeatComber in the lower left corner, and `btrack~` in the lower right corner. The beat tracker with least error is indicated in bold for each noise setting.

the effect of lowering their error by approximately 12 msec.

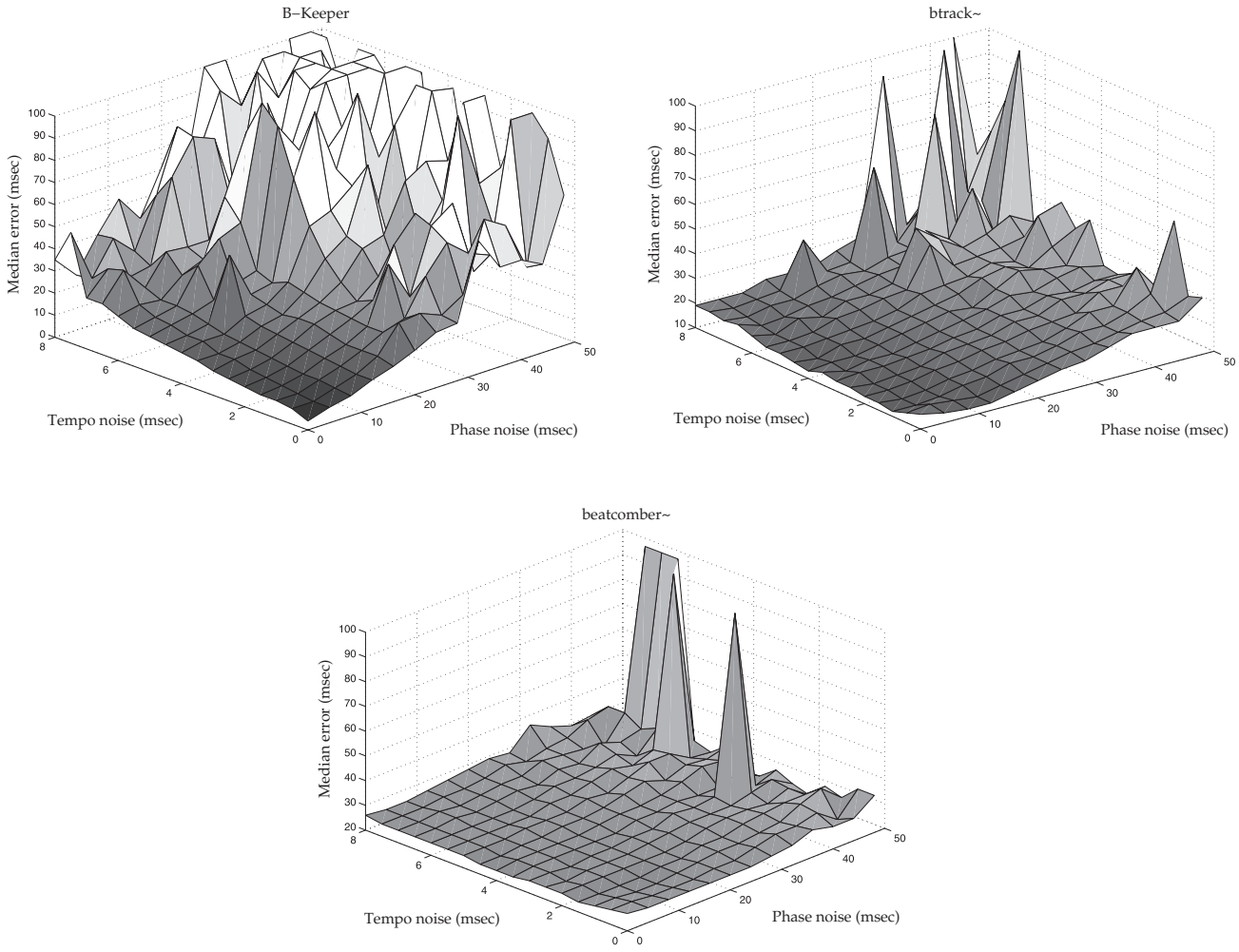
In live performance, the discrepancy between the drum tracker's beat location and the underlying beat will play a crucial role in how well the backing track fits with the drums. Discussing the problem of latency with respect to music performance, Lago and Kon (2004) consider that a delay of between 20 and 30 msec can be tolerated. There is thus a need to minimize any delay between the perceived beat and the output of the system. To quantify this, we calculated the median of the errors between each beat tracker and the drum-machine event times over all trials in which synchronization was maintained for the full 32 bars. Table 1 shows the median error for each beat tracker over all the 25 trials at the lower levels of noise.

Surface plots showing these median timing errors for each beat tracker over the full range of noise parameters tested are shown in Figure 7.

We find that, even with the adjustment for additional latency that other beat trackers introduce, for the lowest levels of noise B-Keeper synchronizes more closely with the drum events than the other beat trackers do. In this zone, the difference between the drum-machine beat times and the click time of B-Keeper tends to be between 10 and 20 msec, a difference that is small enough for this not to be problematic in performance.

Looking at the surface plots in Figure 7, it appears that B-Keeper is slightly less tolerant of high quantities of noise than the other two trackers are. This might be expected as the other beat trackers are designed to be more responsive to strong changes in

Figure 7. Surface plots showing the median error between the beat output times of the stochastic machine for each beat tracker over the full range of noise parameters that were tested.



tempo, whereas B-Keeper is designed to be consistent through passages of syncopation. Nevertheless, it will consistently handle tempo deviations with a standard deviation of 7 msec per quarter note (approximately 1.4 percent of the period) and phase deviation of 20 msec per eighth note (4.0 percent of the beat period).

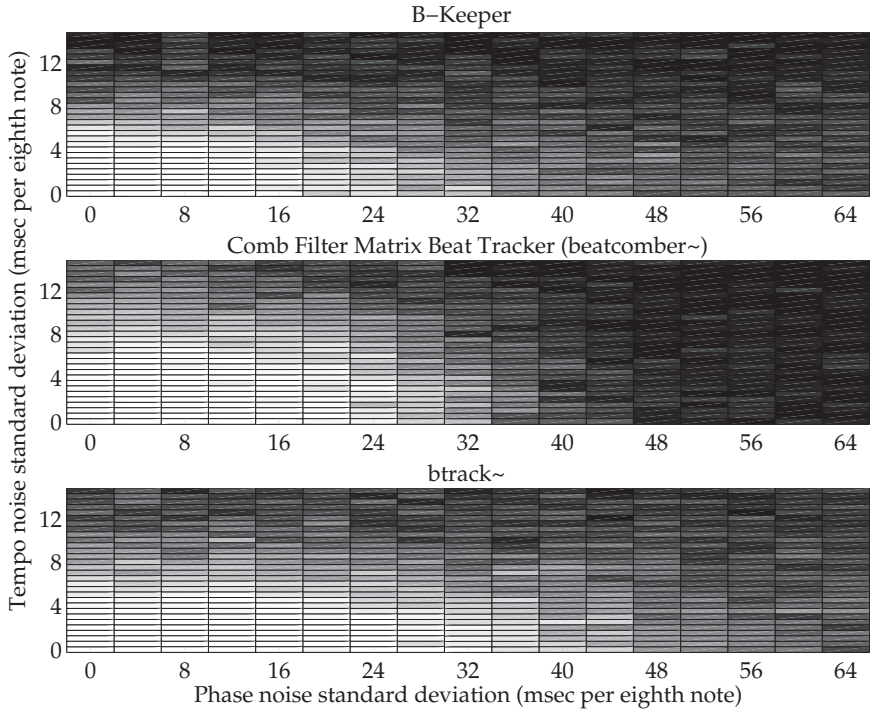
Figure 8 shows how consistent the synchronization is across all trials. The limits of what noise can be accommodated by each tracker are the areas mapped out by the white rectangles where there is consistent synchronization across all 25 runs. These results suggest that there may be a trade-off between low synchronization error and tolerance to noise.

A repository with the files to reproduce the evaluation results is hosted at the SoundSoftware project website (https://code.soundsoftware.ac.uk/projects/b-keeper-stochastic-drum-evaluation/).

Live Performance Experience

By synchronizing a sequencer with a drummer, there are several applications for which B-Keeper can be used. The first is to provide accurately synchronized backing tracks, where audio and MIDI parts play in time with drums in a responsive manner. Over the last two years, the band Higamos

Figure 8. Consistency of synchronization across all beat trackers at various levels of noise introduced. White areas denote 100 percent consistency; the black areas denote 0 percent consistency.



Hogamos (www.higamoshogamos.com) has been experimenting with the system to perform their live set of seven songs. Their performances feature synthesized bass lines and other electronic sounds that would be hard to play live, so the system offers a way to use the original studio parts without the compromise of click tracks and headphones.

The consensus in the band is that the live shows would have changed considerably in character without B-Keeper. Steve Webster, keyboard-player and vocalist, describes the experience by saying it "felt like suddenly having another member of the band, band members that groove and flow with you."

The system has also been used for live looping and improvisation in several sessions with James Sedwards (www.noughtmusic.com), and drummer Jem Doulton (www.jemdoulton.com). Audio parts from guitar and bass were successfully recorded and looped in real time, using a foot pedal to allow the musician to determine which instruments are playing and when they are recorded. This differs from the usual looping set-up, where the loop remains fixed.

Finally, we developed a performance with a robotic glockenspiel (Meckin 2010) to demonstrate how the system brings about possibilities for new musical collaborations. Videos of these two performances can be seen on the B-Keeper–dedicated YouTube channel (www.youtube.com/bkeepersystem).

Conclusions

In this article, we presented a novel system for live drum tracking, designed around a two-process model for tempo and phase tracking, in which a rule-based approach is used to respond to drum events. This is one of the first adaptive sequencer systems for steady-beat music. In order to optimize the system for a variety of playing styles and rhythmic features, such as syncopation and fills, the model's parameters dynamically adapt so that the behavior of the algorithm continually adjusts to the input. We have presented a new evaluation method that tests the quantity of "tempo noise" and "phase-offset

noise" that can be tolerated by the system using a stochastic drum machine.

Our evaluation results indicate that our system is capable of synchronizing more closely to the beat at low levels of "noise" than do two other real-time beat trackers. This is desirable in performance because, when drummers play accurately, we require as close a synchrony between the accompaniment and the musicians as possible.

Future work will address the problem of tempo and phase initialization and error recovery. Alternative beat-tracking algorithms, such as `btrack~` and `beatcomber~`, might be used for such tasks because they are more suited to sudden changes in the musical signal and perform continual tempo estimation across multiple hypotheses. We will extend our investigation of how the system interprets drum events with the aim of improving the range of timing "noise" and rhythmic patterns that the system is capable of following.

The system is available to download at www.b-keeper.org, both for Max/MSP and as a Max for Live device for Ableton Live, allowing musicians to use it as a plug-in over a stereo channel with microphone input from the drums.

Acknowledgments

Andrew Robertson is supported by a Research Fellowship from the Royal Academy of Engineering and the Engineering and Physical Sciences Research Council. Mark D. Plumbley is supported by a Leadership Fellowship (EP/G007144/1) from the Engineering and Physical Sciences Research Council. The authors would like to thank the musicians who took part in testing the software and are grateful to David Nock, James Sedwards, Jem Doulton, Steve Webster, Whetham Allpress, Marcus Efstratiou, Matthew Davies, and Adam Stark for their contributions to the project.

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