Real-Time Analysis of Beats in Music for Entertainment Robots

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Abstract: The dancing actions for entertainment robots are usually designed in advance and saved in a database according to the beats and rhythm of the given music. This research is devoted to developing a real-time algorithm that can detect the primary information of the music needed for the actions of entertainment robots. The computation of the proposed algorithm is very efficient and can satisfy the requirement of real-time processing by a digital signal controller. The digitized music signal is first normalized to make the algorithm robust for miscellaneous music volume. Next, the primary features of the beat for the music are extracted. Based on the extracted features, the algorithm will then identify the occurrence of beats in the music through the use of an optimized classifier. From the accumulated information of the timing for the beats, the algorithm can provide the predicted timing information of the next beat through regression analysis. The type and tempo of the given music can also be derived thereafter. The entertainment robot can thus move or dance according to the information derived by the algorithm. A graphical user interface (GUI) program in LabVIEW is also utilized to observe and verify the analysis results. In this study, the ratio for correct beat detection is greater than 85%. The prediction ratio for the correct timing of beats is over 80%, and it is 100% correct for both music type and music tempo.

Keywords: beats; entertainment robot; fast Fourier transform (FFT); regression analysis; rhythm; standard of octave

Introduction

Robots have been developed to serve human beings in various tasks. ABI research reported that entertainment robots that are designed to amuse users have had an average annual growth rate of 50% during the past six years in the Asian market [1]. Among miscellaneous entertainment robots, robots that can move or dance in response to a particular piece of music are the ones that customers find most attractive. Conventionally, the actions of such robots were usually scheduled in advance according to the beats and rhythm of a given piece of music existing in the robot's database. In such cases, the robot can only respond to music in its database, and extra memory space is required for this kind of robot. In order to overcome these drawbacks, this research is dedicated to the development of a real-time algorithm that can, from the music which the robot is responding to, extract the primary information needed for the actions of an entertainment robot.

Music is composed of components such as beats, rhythm, tempo and type. Some of the components are time-varying and nonstationary, and this is why the music is pleasant to hear. Human beings have the ability to recognize the basic components in music and can instinctively act in response to music. However, it is challenging for artificial systems such as computers and robots to respond in a similar way. A number of research studies have been devoted to the analysis and extraction of major features in music. Scheire developed a method that utilized band-pass filters and a filter bank to analyze the tempo of music, and a specific algorithm was also designed to predict the occurrence of subsequent beats [2]. In another research, Eck proposed a rule-based approach to identifying the beats in the music. The detected beats were then compared with those marked intuitively by human listeners [3]. Goto presented a real-time beat tracking system based on the onset time, chord changes and drum patterns in the music [4-6]. Jensen and Andersen extracted certain features from the music to identify the onset of particular notes. The beat location was then determined by the most probable beat intervals. This proposed technique performs well for a wide variety of popular music [7]. In reference [8], Sethares *et al*. presented methods based upon a Bayesian decision framework and employed a gradient descent approach to track the beats in musical performance. One probabilistic model proposed by Lin *et al*. involved estimating tempo and timing signature together in order to detect and track beats in music. [9]. Klapuri *et al*. utilized a comb filter and another probabilistic methods based on *a priori* music knowledge to extract musical features and to estimate the timing signature in various hierarchical metrical units [10]. In reference [11], a methodology is presented for predicting the beats in a particular piece of music according to the note onsets determined by a weighted linear combination of the sub-band features in the spectrum of the music signal. Mikel's study is devoted to estimating the metrical structure of a piece of music based on the generation of a beat similarity matrix [12]. In order to model the dancing action of robots, Aucouturier *et al*. utilized the characteristics of chaotic itinerancy for the bio-inspired FitzHugh-Nagumo neuron model [13]. These studies have provided a variety of approaches for the analysis of music. However, because they depend on large amounts of computation, most of the proposed methods require the use of desktop computers or costly digital signal processor units. In addition, very little of the research could satisfy the requirement of real-time analysis without the support of a music database.

The objective of this research is to develop a real-time algorithm for music analysis that possesses a low computation load and can satisfy real-time requirements without the inclusion of a music database in a general digital signal controller. The proposed algorithm has been implemented and tested on dsPIC™ (Microchip Technology Inc.). The algorithm can detect the timing of beats in musical input in real time, and the predicted timing of succeeding beats can also be provided by regression analysis. Based on information about the timing of beats, the type and tempo of the given music can then be derived. In addition, a graphical user interface (GUI) program in LabVIEW is also developed to observe and verify the results of the analysis.

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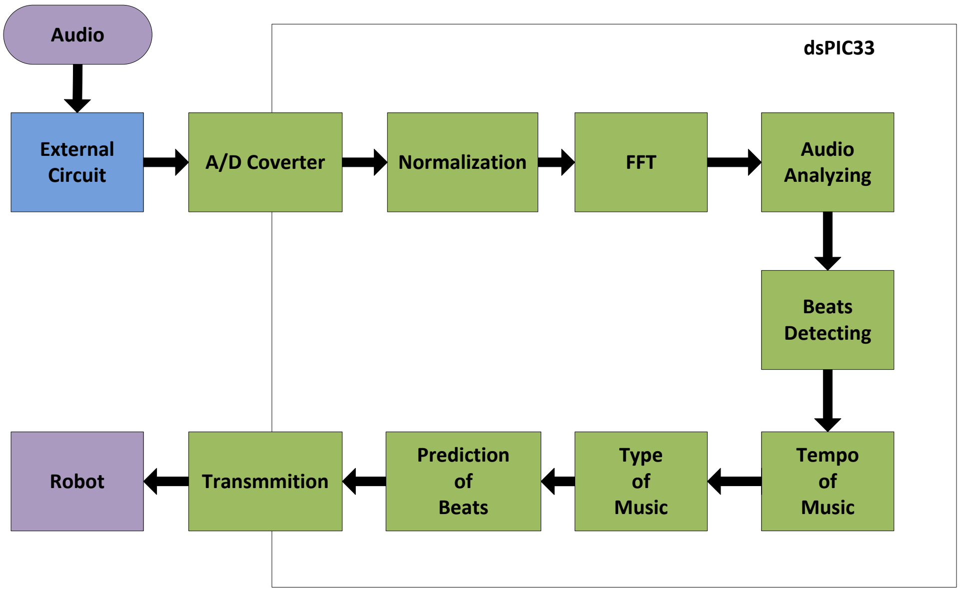


Figure 1. Flow diagram of the proposed system.

Methods

The flow diagram of the proposed system is demonstrated in Figure 1. The system can be divided into two units. They are the analog processing unit for the input audio signal and the digital processing unit for the digitized audio signal. For the analog processing unit, the input music signal from the line-in plug is first pulled up to be of positive potential. The pulled-up signal is then filtered by a bandpass filter (BPF), which is composed of a highpass filter (HPF) and a cascaded lowpass filter (LPF). Single-supply operational amplifiers (OP AMP) are utilized for the circuit design in the analog processing unit. An analog-to-digital converter (ADC) in the digital processing unit is utilized to digitize the analog signal. In the digital processing unit, the digitized signal is first normalized by a formula of linear projection. Next, the respective energy in eighteen sub-bands of the signal is derived by fast Fourier transform (FFT). The derived energy is the primary element of the algorithm for beat detection. The timing for each beat is then utilized to determine the tempo, type and the timing prediction of the followed beat in the music. A more detailed description follows.

Processing the analog music signal

The digital signal controller utilizes single supply for its operation. It is desirable that the condition of the signal for the music be in a single-supply mode, because this reduces the complexity of the printed circuit board (PCB) and simplifies the circuit design. Therefore, single-supply OP AMPs were adopted in the analog processing unit for this research. Music is composed of sound waves emanating from a variety of musical instruments, and each instrument has its specific timbre and characteristic spread in the spectrum. In order to reduce the overall computation burden of the digital processor, the frequency range that the system is required to process must be taken into consideration in advance. As the fundamental frequency for most musical instruments in rhythmic music ranges from around 20 Hz to 2000 Hz [14], this range was adopted for the -3dB cutoff frequency of LPF and HPF for the music signal. The resulting effect on the signal conditioning of the analog processing unit is shown in Figure 2, in which the left figure shows the original music signal and the right figure shows the processed output signal. It can be seen that the signal has been elevated to positive potential and the high-frequency components in the original signal have been removed by the analog processing unit.

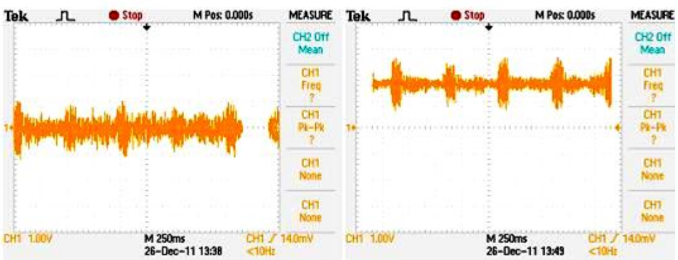


Figure 2. The original signal (left); the processed signal (right).

Normalization

Normalization is a way to make the proposed algorithm for the detection of beats more robust for various volumes of the input audio signal. In the digital processing unit, the digitized signal is normalized before any further processing. The formula is based on linear projection and is given in Equation (1):

$$\hat{x}[n] = \frac{b2 - b1}{a1 - a2} \cdot x[n] + \frac{a1 \cdot b1 - a2 \cdot b2}{a1 - a2}, \qquad (1)$$

in which $\hat{x}[n]$ denotes the normalized signal, $x[n]$ is the original digital signal; and $b1$ and $b2$ represent the minimum and maximum threshold desired in digital presentation, whereas $a1$ and $a2$ denote the maximum and minimum value of $x[n]$ within a window of 0.064 seconds. Figure 3 demonstrates the result for the original signal (upper) and for the normalized signal (lower).

Energy analysis

Not only should the signal be processed without much distortion but also the amount of operation in the chip should be reduced to satisfy real-time requirements. In this research, the sampling frequency of ADC is 4000 Hz. A 256-point FFT with Hamming window is adopted for spectrum analysis, which implies a frequency resolution of 15.625 Hz. As observed in the dynamic spectrum of the music, it can be seen that the energies of some specific frequency bands appear to be considerable in the presence of beats. The energy bands are based on the octave standards proposed by the American National Standard Institute (ANSI) [15]. The relationship between the frequency indices of FFT and the octave standards is shown in Table 1. The energy for specific bands can be calculated using the following equation:

$$P = \sum_{k=i}^{m} |X[k]|^2 = \sum_{k=i}^{m} \left[X_R^2[k] + X_I^2[k] \right], \qquad (2)$$

in which $X[k]$ represents the Fourier transform of $\hat{x}[n]$, P denotes the energy of the specific band indicated by the indices from i to m, $X_R[k]$ is the real part of $X[k]$, and $X_I[k]$ is an imaginary part of $X[k]$. Finally, eighteen energy bands in the music signal are represented by the array $\mathbf{B}[m]$ as follows:

$$\mathbf{B}[m] = \left[P_1[m] \;\; P_2[m] \cdots\cdots P_{17}[m] \;\; P_{18}[m] \right]. \qquad (3)$$

Table I: The relationship between FFT and the standard of octave.

FFT		Standard of octave	
Frequency indices	Frequency (Hz)	Center frequency (Hz)	Frequency (Hz)
2	31.25	31.5	28.2~35.5
3	46.875	50	44.7~56.2
4	62.5	63	56.2~70.8
5	78.125	80	70.8~89.1
6~7	93.75~109.375	100	89.1~112
8~9	125~140.625	125	112~141
10~11	156.25~171.875	160	141~178
12~14	187.5~218.75	200	178~224
15~18	234.375~281.25	250	224~282
19~22	296.875~343.75	315	282~355
23~28	359.375~437.5	400	355~447
29~35	453.125~546.87	500	447~562
36~45	562.5~703.125	630	562~708
46~57	718.75~890.625	800	708~891
58~71	906.25~1109.37	1000	891~1120
72~90	1125~1406.25	1250	1120~1410
91~113	1437.5~1765.65	1600	1410~1780
114~128	1781.25~2000	2000	1780~2240

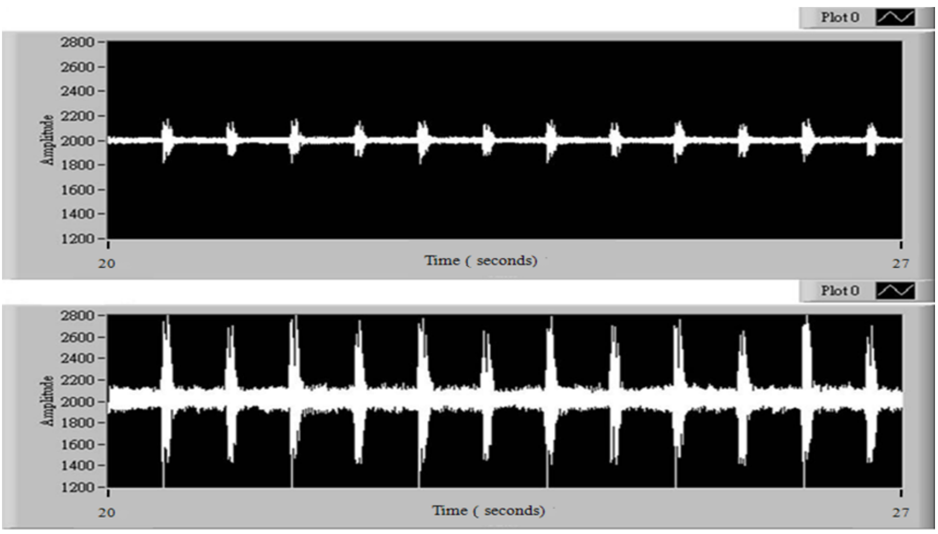


Figure 3. Upper: $\hat{x}[n]$, lower: $x[n]$.

Beat detection

Feature extraction

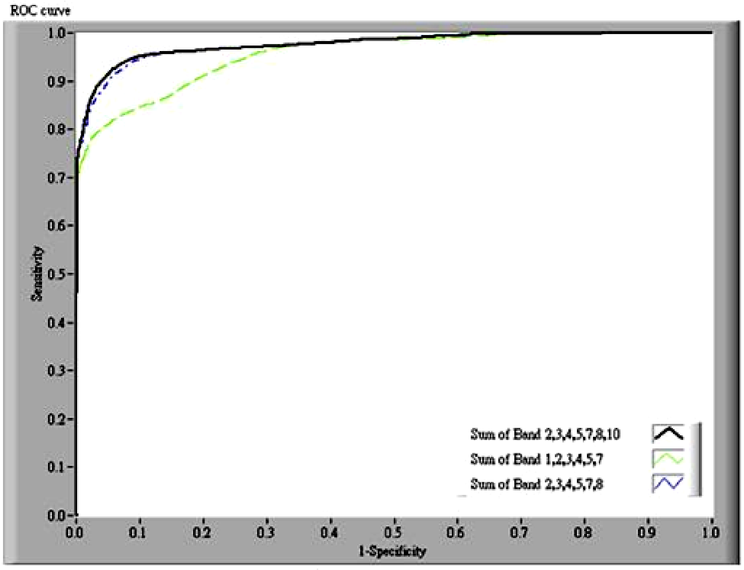
The energy at some bands can be found to be considerable when a beat occurs. To determine the presence of beats, information about the bands of beats and the bands of non-beats should be analyzed in advance. With the help of Cakewalk™ (a software for processing music that can display all the information in the music in octave standards), the segments for beats and non-beats in the music are extracted to determine the decision rule for further analysis. The music is cut into segments and collected into two groups, one for beats and the other for non-beats. We then evaluate the eighteen energy bands of selected features using principal component analysis (PCA) and receiver operating characteristic (ROC) curves. The PCA results are shown in Table 2. It can be seen that a cumulated variance of 80% can be attained with seven eigenvalues. Thus the energy sum of seven primary energy bands is selected to be one of the features for the classification for beats or non-beats, and the resulting ROC curves for different sums of energy are shown in Figure 4. From the area under the curve (AUC), the energy sum of bands 2, 3, 4, 5, 7, 8 and 10 in the array $\mathbf{B}[m]$ is a feasible feature and is selected to be the first feature for the classification of beats or non-beats. The energy distribution for the first feature is demonstrated in Figure 5. Since the features of beats and non-beats overlap, there is a need to find a way to discriminate between beats and non-beats so that they may be properly classified. To improve classification, adding another feature may be helpful. As the total energy of beats was much larger than that of non-beats, eighteen energy bands in $\mathbf{B}[m]$ are sorted in an ascending order and are denoted by $\hat{\mathbf{B}}[m]$ as follows:

$$\hat{\mathbf{B}}[m] = [Q_1[m]\ Q_2[m] \cdots\cdots Q_{17}[m]\ Q_{18}[m]], \tag{4}$$

where $Q_i(t)$, $i = 1, 2, \ldots 18$, represents the sorted band.

Table 2. The result of principal component analysis.

Principal component	Eigenvalue	Cum. variance (%)
1	6.197106	34%
2	2.337917	47%
3	2.080548	59%
4	1.396445	67%
5	0.990206	72%
6	0.675946	76%
7	0.638761	80%
8	0.590391	83%
9	0.528705	86%
10	0.47125	88%
11	0.422939	91%
12	0.38889	93%
13	0.364556	95%
14	0.234352	96%
15	0.209889	97%
16	0.180129	98%
17	0.165939	99%
18	0.126029	100%



Measure	AUC	CI range
Band(2,3,4,5,7,8,10)	0.992	0.990–0.993
Band(2,3,4,5,7,8)	0.991	0.989–0.992
Band(1,2,3,4,5,7)	0.955	0.952–0.958

Figure 4. ROC curves with different features.

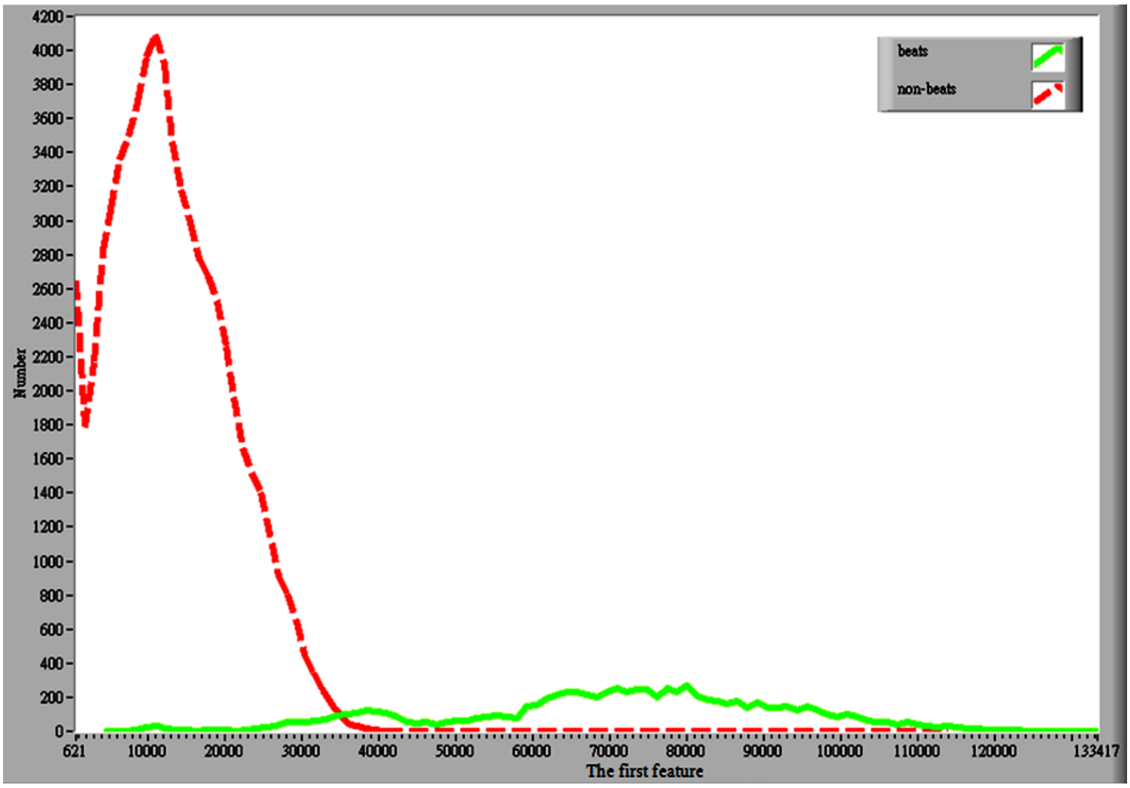


Figure 5. The energy distribution for the first feature. The solid-line represents the beat, and the dashed-line represents the non-beat.

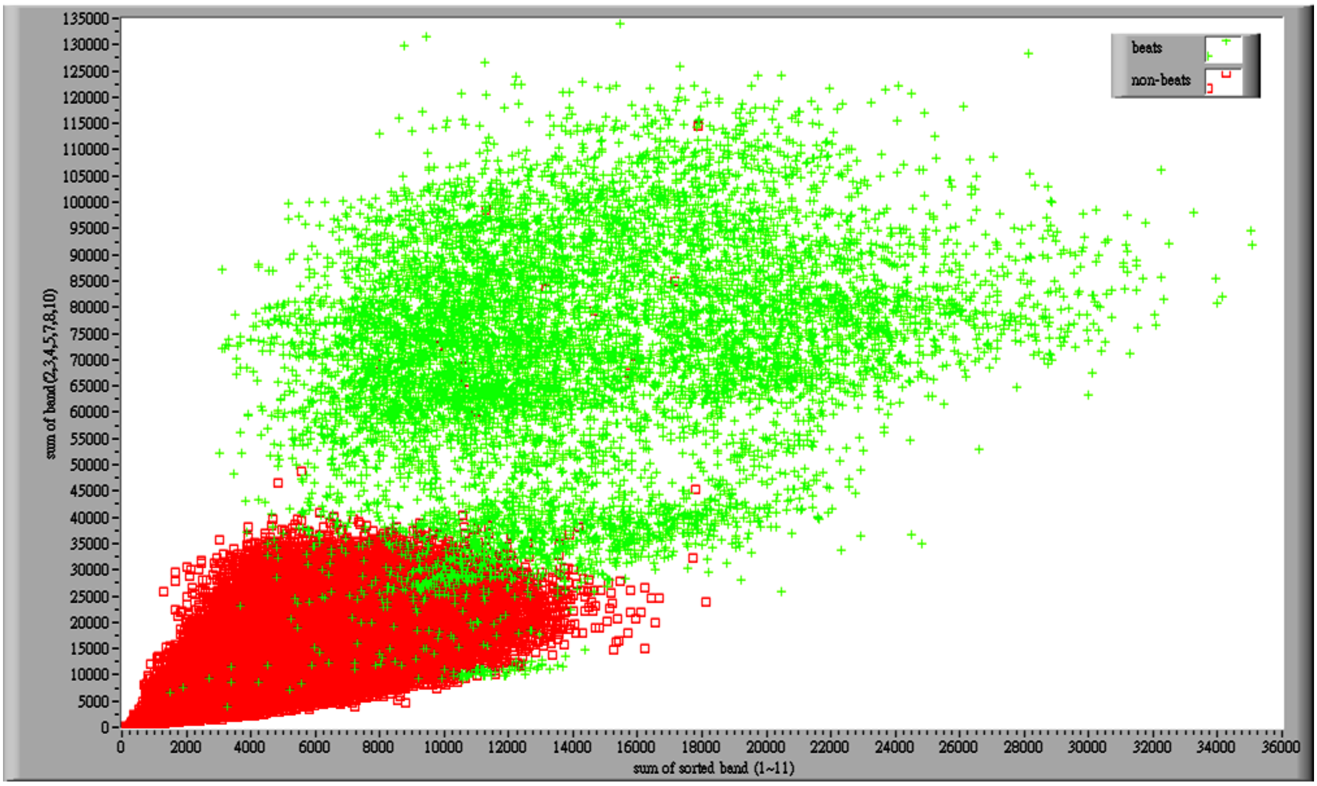


Figure 6. Scatter diagram for the features selected from 20 songs. The cross (+) represents the beats, the check (□) represents the non-beats.

Since the features should be independent of each other, only the bands that are not included in the first feature are considered. Next, a similar approach to that used for the first feature is applied to the remaining eleven energy bands. The energy sum for the eleven bands is thus selected to be the second feature, and the scatter diagram for the two features selected from 20 songs is derived in Figure 6.

Decision rule

As shown in Figure 6, it can be seen that an overlapping area still remains in the scatter diagram. Therefore the decision rule must be defined in an optimal way. The popular discriminant analysis (DA) is selected for the purposes of discrimination in this research. Four types of DA are adopted for performance comparison. They are denoted as linear, diaglinear, quadratic and diagqudratic DA. Linear DA fits a multivariate normal density to each group with a pooled estimate of covariance. Diaglinear DA is similar to linear DA except for the diagonal covariance matrix estimate. Quadratic DA fits multivariate normal densities with covariance estimates stratified by group. Diagqudratic DA is similar to quadratic DA but it has a diagonal covariance matrix estimate. Each type of DA was tested and the respective decision threshold is illustrated in Figure 7. The classification results for each DA were tested with the ROC curve and the result is shown in Figure 8. From the demonstrated results, the performance of diagqudratic DA is evaluated to be the DA which is optimal for the detection of beats in music.

Even though the diagqudratic DA has the best performance, the probability of false positives still remains. To overcome this deficiency, a gray zone consisting of 0.1% of the fault-tolerant rate is defined to decrease the error of classification. A decision would not be taken into consideration if the features were located in the gray zone. The beat detection is defined as follows:

$$\begin{aligned} D &= 7.40048 + 0.000257888x + 6.66049\times10^{-5}y \\ &-5.61383\times10^{-8}x^2 - 7.83078\times10^{-9}y^2, \end{aligned} \tag{5}$$

and

$$O(t) = \begin{cases} 1, & for\ \ D > 0.45 \\ 0, & for\ \ D < -0.45 \end{cases}, \tag{6}$$

in which x is the value of the second feature, and y is the value of the first feature. The symbol $O(t)$ represents the detection of beats, the value 1 represents that a beat is detected and 0 signals a non-beat.

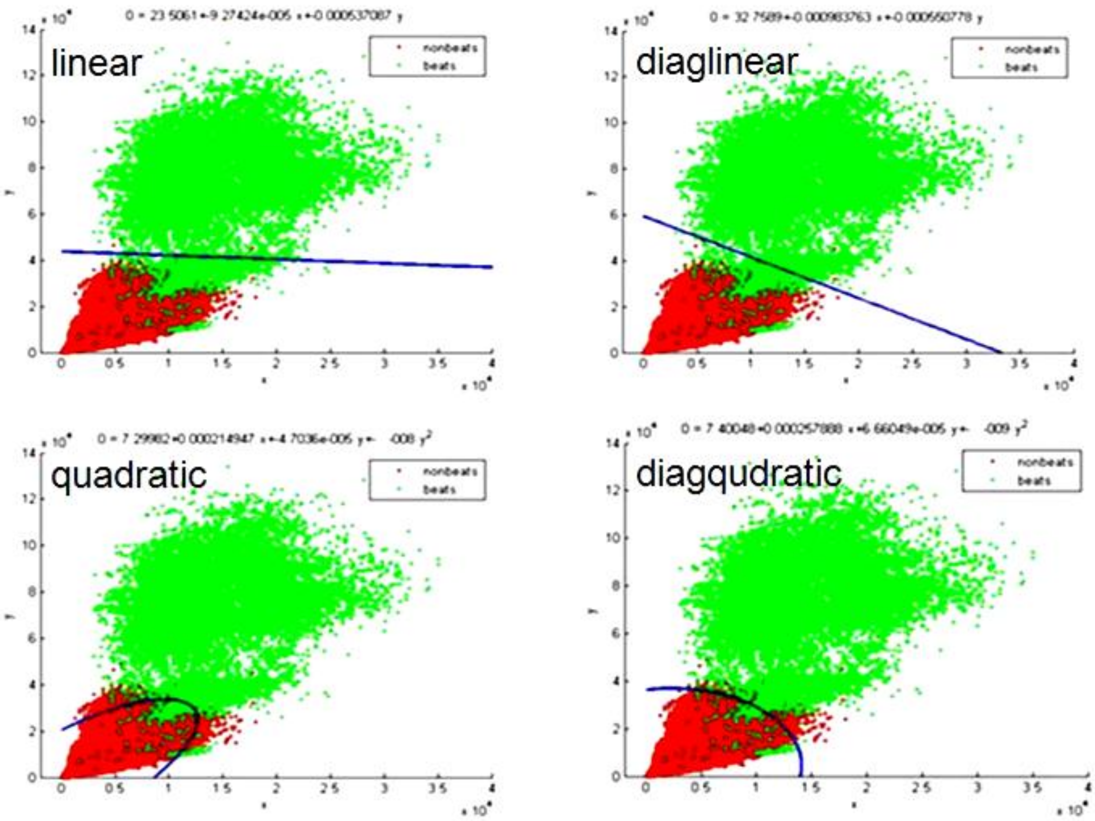
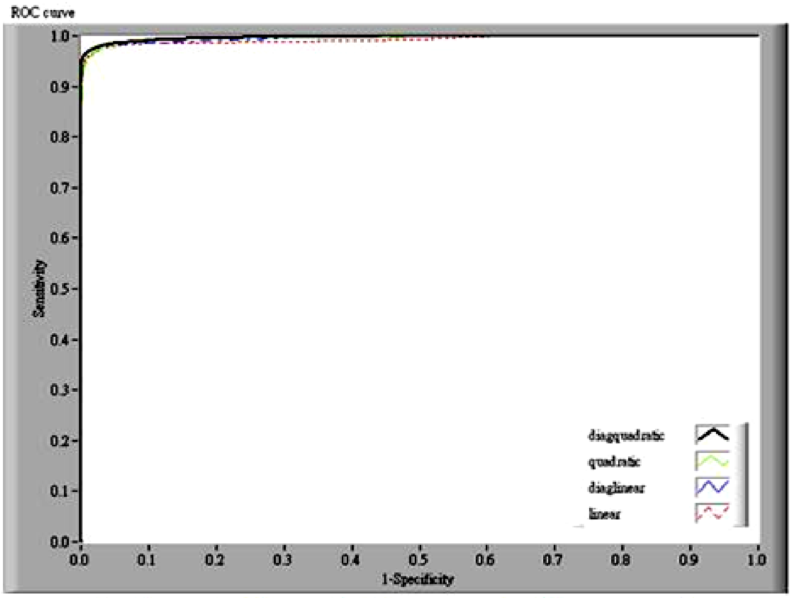


Figure 7. The decision threshold for each type of discriminant analysis.



Measure	AUC	CI range	Sensitivity	Specificity
diagqudratic	0.997	0.996 – 0.997	0.972	0.986
diaglinear	0.996	0.996 – 0.997	0.914	0.999
qudratic	0.996	0.995 – 0.996	0.965	0.983
linear	0.993	0.993 – 0.994	0.871	0.999

Figure 8. ROC curves for each type of discriminant analysis.

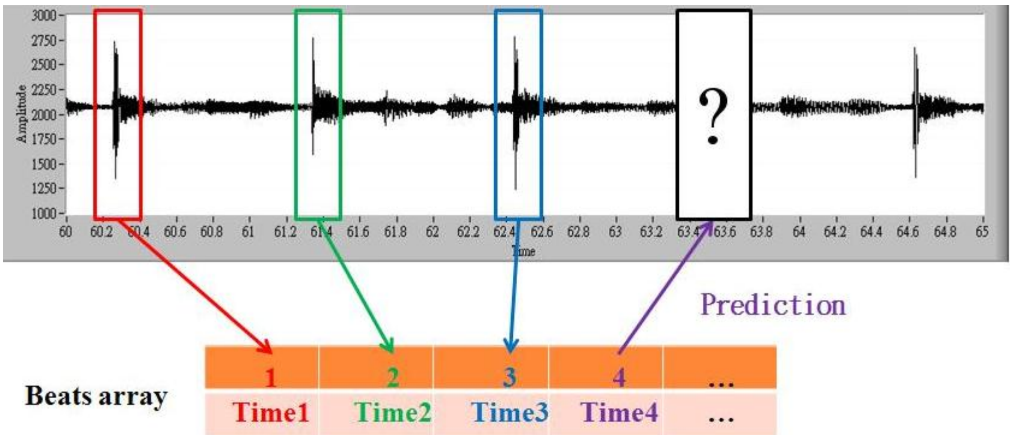


Figure 9. Depiction of beats prediction.

Prediction

Linear regression exists in a variety of types, depending on the number of independent variables. In this research the simple regressive equation (only one independent variable) is utilized to predict the next beat desired. The next beat's position would be predicted by the positions of three adjacent beats (as depicted in Figure 9). The equation can be presented as in Equation (7):

$$y_i = B_0 + B_1 \cdot x_i, \tag{7}$$

with

$$\overline{X} = \frac{\sum_i x_i}{3}, \quad \overline{Y} = \frac{\sum_i y}{3}, \tag{8}$$

and

$$B_1 = \frac{\sum_i x_i \cdot y_i - 3 \cdot \overline{X} \cdot \overline{Y}}{\sum_i x_i^2 - 3 \cdot \overline{X}^2}, \quad B_0 = \overline{Y} - b_1 \cdot \overline{X}. \tag{9}$$

In brief, x_i is the number of beats in the first array of beats, y_i is the timing of beat position, $\overline{X}$ is an average of set of three beats, $\overline{Y}$ is an average of a set of three beat positions, B_0 is the intercept of regression, and B_1 is the coefficient of regression.

Tempo and Type of Music

Using the developed algorithm, the first beat of each measure in 3/4 time music and each beat in 4/4 time music can be specified.

Tempo means the number of beats per minute in the music. The tempo of music can be computed by the interval of beats. As the developed algorithm can recognize the tempo in 4/4 time music and one-third of the tempo in 3/4 time music, the type of music can consequently be inferred.

Results

In this research, twenty songs (ten of which are in 3/4 time and ten of which are in 4/4 time) have been chosen for performance testing. The test results for a randomly selected set of 17 songs are summarized in Table 3. The tempo of each song is successfully detected within 10% of error, and the recognition of music type is also achieved with a 100% degree of accuracy. Additionally, the rate of beat is predicted accurately 80% at least of the time within plus or minus 20 milliseconds of error.

This algorithm can be utilized to detect the beats of music, recognize the type and tempo of music, and predict where the next beat is located. In addition, all the results could be displayed and verified by a developed graphical user interface (GUI) program in LabVIEW. The GUI program is as shown in Figure 10.

The algorithm is implemented in dsPIC^{TM} with a clock of 40 MHz. The execution time for the proposed algorithm is 65.27 milliseconds, in which the computation of FFT occupies 64 milliseconds. Hence, all the analysis can be executed in real-time.

Conclusion and Discussion

The objective of this research is to develop a real-time algorithm that can analyze beats without the need of a database. The digital processing controller dsPIC^{TM}, which is low in cost but high in performance, is selected to implement the proposed algorithm in this research. To counteract the computation load in the chip, we have developed an efficient algorithm to analyze the information in the music. Energy related features and a DA classifier with a gray zone are proposed to identify the beats and non-beats in the music. Among various DA classifiers, diagqudratic DA is evaluated to have the best performance. In addition to detecting the musical beats, the proposed algorithm also possesses the ability to recognize musical tempo, music type and to predict following beats.

Table 3. Performance of analysis module (√: correct and satisfied).

Songs with 3/4 time and 4/4 time	Detection rate	Prediction rate (±20 ms)	Music tempo	Music type
The one dwight	100	97.43	√	√
Never too late	97.18	96.22	√	√
Stars over Texas	100	95.65	√	√
Jump	98.15	95.10	√	√
Strawberry wine	97.64	93.67	√	√
Disturbia	93.55	92.49	√	√
You look so good	97.63	92.10	√	√
Edwin McCain ill be	95.48	89.95	√	√
Bridge to cross	96.76	87.45	√	√
Quarter call	97.02	86.73	√	√
Wanted	95.00	85.63	√	√
All the lovers	91.90	84.27	√	√
Rain on me	85.87	82.87	√	√
Tush	89.80	82.85	√	√
Lucille	97.46	82.48	√	√
Just dance	88.40	82.20	√	√
Please come home	92.05	81.89	√	√
Don't lie	90.82	80.58	√	√
You rock my world	90.61	80.58	√	√
Poker face	85.12	80.10	√	√

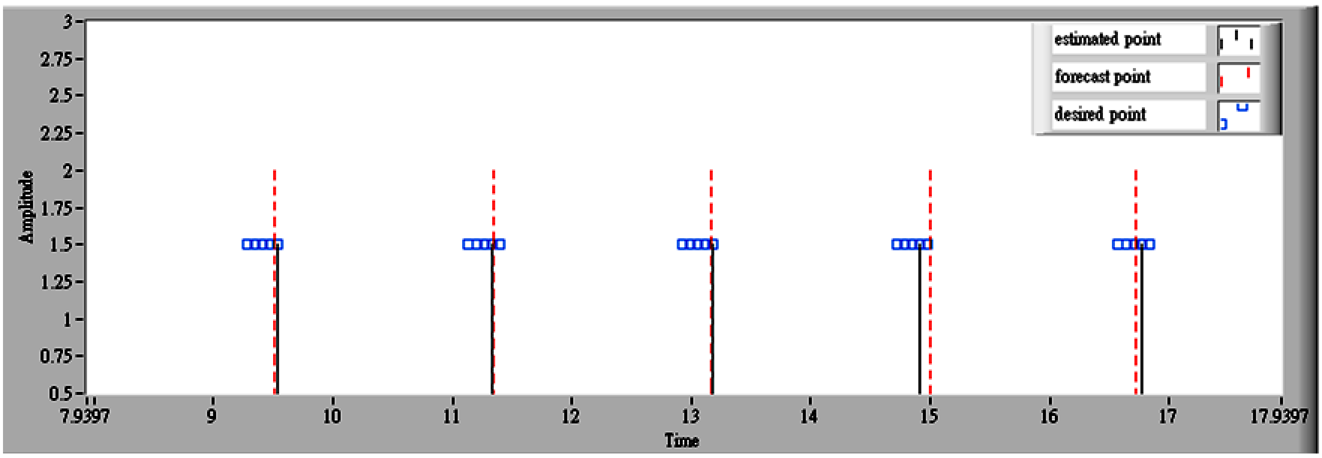


Figure 10. The interface of analysis module: the check is the desired point of beat. The solid-line is the estimated point of beat, and the dashed-line is the forecast point of beat.

In the proposed method, the analysis results are determined by the accuracy of beat detection. The beat detection is closely related to the quantity of training data. In order to enhance the stability of the system, adding training data would be a promising route for further research. Moreover, the dimension of feature space could also be increased to improve detection accuracy.

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