

Piano Pedaller: A Measurement System for Classification and Visualisation of Piano Pedalling Techniques

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ABSTRACT

This paper presents the results of a study of piano pedalling techniques on the sustain pedal using a newly designed measurement system named Piano Pedaller. The system is comprised of an optical sensor mounted in the piano pedal bearing block and an embedded platform for recording audio and sensor data. This enables recording the pedalling gesture of real players and the piano sound under normal playing conditions. Using the gesture data collected from the system, the task of classifying these data by pedalling technique was undertaken using a Support Vector Machine (SVM). Results can be visualised in an audio based score following application to show pedalling together with the player's position in the score.

Author Keywords

Piano pedalling, playing techniques classification, musical gesture visualisation

ACM Classification

H.5.2 [Information Interfaces and Presentation] User Interfaces, I.5.5 [Pattern Recognition] Implementation — Interactive systems.

1. INTRODUCTION

The role of pedalling in piano performance is regarded as “the soul of the piano”, according to Russian pianist Anton Rubinstein. Pianists can add variations to the tones with the help of three pedals. However, the role of pedalling as an instrumental gesture to convey different timbral nuances has not been adequately and quantitatively explored, despite the fact that the acoustic effect of the sustain pedal on piano sound has been studied [11]. Since the pedalling parameters are difficult to estimate from the audio signal [6], reliable recognition of pedalling techniques that com-

prise when and how to depress or release the pedals would be helpful for applications in areas of pedagogy, interactive performance, music information retrieval and so on. Therefore we present a non-intrusive measurement system that can capture pianists' pedalling gesture and piano sound simultaneously. The classification results of these movements and the piano sound can be used in a score following system for visualisation.

The use of the pedals was not marked in musical scores before the 1790s [19]. In the beginning, it was considered gimmicky by serious musicians [9], but soon in the 19th century composers like Chopin and Liszt took advantage of the modern technique and employed the usage of the pedals actively in their works [10]. Debussy and Scriabin rarely notated pedalling, but they and later composers continued to find new sounds through the assumed use of the pedals [18]. Modern grand pianos have three pedals, which from left to right are commonly referred to as the *una corda* pedal, the *sostenuto* pedal and the *sustain* pedal. The *sustain* pedal is the most commonly used one. It lifts all dampers and sets all strings into vibration due to sympathetic resonance and the energy transmission via the bridge. This allows the strings to keep vibrating after the key is released.

Pedalling techniques can be varied from timing and depth of pedal press and release. Especially for the *sustain* pedal, there are a variety of ways to apply it, ranging from partial pedal to continuous fluttering pedal. Professional pianists employ different fractions of partial pedal to colour the resonance subtly. Three or four levels are commonly defined from the continuous changes of pedal in order to interpret the pedal usage. Flutter pedalling is similar to half-damping, which consists of very quick and light movements in order to reduce accumulating sound. However, no compositional markings exist to indicate the variety of techniques on the *sustain* pedal [20]. This requires a visualisation system to classify the pedalling techniques first and then represent them using custom notations. Our study was implemented on the *sustain* pedal. Onset and offset time were detected at first. Four pedalling techniques (quarter, half, three-quarters and full pedal) were classified using continuous pedal position changes in one dimension as inputs to a SVM algorithm. They can be demonstrated with a music score in our visualisation application.

In this paper, we first discuss related works on gesture sensing in piano performance (Section 2). Then we present our system architecture (Section 3) and implementation (Sec-



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tion 4). We finally conclude the paper and how our system could be applied in the future (Section 5).

2. RELATED WORK

In many studies of musical gestures, systems are developed to be in place for multi-modal recordings in order to capture comprehensive parameters, such as timing, dynamics and motion in musical performance. There has been a significant number of projects focusing on piano performance.

Most related projects focus on hand and arm gestures. Hadjakos et al. [7, 8] developed a piano pedagogy application that measures the movement of hand and arm and generates feedback to increase piano students’ awareness of their movement. McPherson [12] created a portable optical measurement system for capturing continuous key position and providing multicolour LED feedback on any piano. Apart from the use of specialised sensors, commercial motion capture systems have been employed to augment piano performance. Brent [3] developed the *Gesturally Extended Piano*, an augmented instrument controller that tracks performer movements using infrared motion capture system in order to control real-time audiovisual processing and synthesis by pre-defined gestures. A similar approach has been used by Yang et al. [23] where Microsoft Kinect was used and visual feedback was provided.

Recent advances in machine learning bring real time performance, robustness and invariance in modelling data. This makes machine learning increasingly capable of analysing live, expressive gestural input [4]. Gillian and Nicolls [5] created an improvisation system for piano where Kinect data feeds a machine learning based classification algorithm. This allows pianist control high level musical switches by performing pre-defined static postures which are separate from pianistic gesture vocabulary. Given that, Van Zandt-Escobar et al. [24] developed *PiaF*, a prototype that studies variations in the interpretation of gestures that are inside the range of the pianists’ practice.

None of these projects considered the inclusion of pedalling techniques as part of gesture sensing. Bösendorfer CEUS piano has the ability to record continuous pedal position, which was used by Bernays and Traube [2] as one of the performance features to investigate timbral nuances. However, it is rather expensive and unable to be moved easily, which remains a barrier to wider adaptation. To overcome this, the PianoBar [1] is a convenient and practical option for adding MIDI capability to any acoustic piano but its pedal sensing is discrete that only provides on/off information. McPherson and Kim [13] modified the PianoBar in order to provide a continuous stream of position information, but thus far few detailed studies have made use of the pedal data. These problems have motivated our work to develop a system that can be portable, self-contained, low-cost and non-intrusive to measure continuous pedalling gesture and analyse it using a SVM-based machine learning method. The system could contribute to various types of sensing for piano and other keyboard instruments.

3. ARCHITECTURE

Piano Pedaller has been designed in order to be used in different piano performance scenarios without a complex setup process. Figure 1 illustrates the schematic overview of our study which has three main components communicating with each other:

1. *Data Capture*: This portion collects the sensor data of the sustain pedal movement and the audio data while

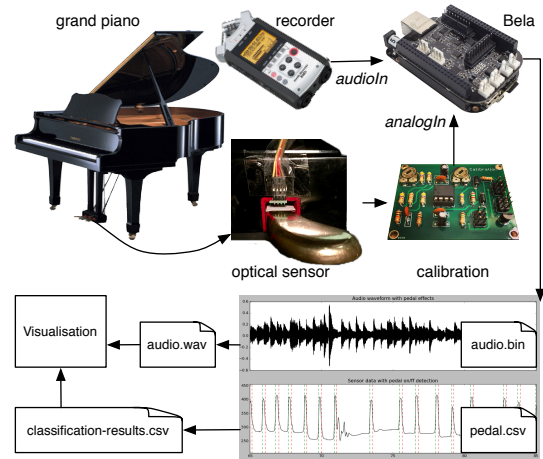


Figure 1: Schematic overview.

playing piano excerpts with pedal effects using Bela¹ which is an open-source embedded platform for real-time, ultra-low-latency audio and sensor processing on the BeagleBone Black [14].

2. *Classification*: The pedal sensor data is sent to signal processing algorithms, which compute the onset and offset time of each pedalling technique. Features are extracted from every segment when the pedal is depressed. Based on these features, classification results are derived using a SVM algorithm and stored for visualisation.
3. *Visualisation*: Classification results of piano pedalling techniques can be mapped to different pedal notations. Since these notations are time-aligned with the recorded audio, they can be presented in a score following system which aligns the audio recording with a musical score of the same piece. Therefore when and how the pedal is used can be visualised with which notes in the score are being played according to the audio.

4. IMPLEMENTATION

Based on the above architecture, we deployed Piano Pedaller on the sustain pedal of a Yamaha baby grand piano. A pianist was asked to perform ten excerpts of Chopin’s piano music based on the scores where the sustain pedal should be pressed to what extent in each music phrase was notated by the experimenter. The audio and the gesture data were recorded to files. The gesture data was labeled according to the notated score in order to provide a basic ground truth dataset. Here we describe the newly designed measurement system for data capture, the classification based on the SVM method, and the visualisation application.

4.1 Data Capture

In the current scenario we focused on tracking the pianist’s pedalling techniques of the sustain pedal in a non-intrusive way. For this purpose, near-field optical reflectance sensing was used to measure the position of the pedal. A pair of Omron EESY1200 sensors, which include an LED and a phototransistor in a compact package, were mounted in the pedal bearing block. The output voltage is proportional to incoming light and roughly follows the inverse square of

¹<http://bela.io/>

the pedal-sensor distance. A removable white sticker was affixed to the pedal in order to reflect enough light to be measured reliably. The output voltage was calibrated through a custom-built Printed Circuit Board (PCB) in order to improve response speed and ensure stability.

Thereafter our data was collected using the Bela platform [14] which provides stereo audio input and output, plus channels of 16-bit analog-to-digital converter (ADC) and 16-bit digital-to-analog converter (DAC) for sensors and actuators. It combines the resources of an embedded Linux system with the performance and timing guarantees typically reserved for dedicated digital signal processing (DSP) chips and microcontrollers. Audio and sensor data can be sampled and synchronised to the same master clock. Our sensor data was recorded at 22.05kHz sampling rate using the analog input of Bela. The piano sound was simultaneously recorded at 44.1kHz through a recorder as the audio input to Bela as well. These two types of signal data were aligned and stored as CSV files and binary files respectively.

4.2 Classification

For our implementation, we used the sensor data alone to do the classification. Despite pedal position was measured in a continuous space, classification of pedalling as discrete types may benefit applications such as transcription and visualisation. Four pedalling techniques (quarter, half, three-quarters and full pedal) were classified using a supervised learning method. Since the usage of a pedalling technique almost never remains the same even for the same pianist, a machine learning method could efficiently learn an optimal threshold for classification in a data-driven manner.

The classification task operates in three separate phases: a pre-processing phase, in which the pedalling onset and offset are detected and segments are defined; a training phase that learns a function between input variables and discrete labels using SVM; and a testing phase that assigns an output label to a new input sample.

4.2.1 Pre-processing

The Savitzky-Golay filter is a particular type of low-pass filter, well-adapted for data smoothing [17]. It has been used to smooth time-series data collected from sensors such as electrocardiogram processing [15]. We applied this filter to the sensor data in order to avoid spurious detection of pedalling onset and offset.

Based on the filtered sensor data, pedalling onset and offset time were found by comparing with a threshold, below which is the onset and above is the offset. Instead of manually setting a threshold, the threshold was decided by choosing the minimum value from a peak detection algorithm. It was noted that there would be false-positive detection of pedalling onset and offset because of the effect of fluttering pedal. Hence we calculated the time interval between each pedal onset, and then set a timing as the fluttering threshold. If the time interval between two detected onsets is below the fluttering threshold, the latter onset followed the former one in such a short time that should be considered as part of the data within the same pedal usage instead. We repeated the process to remove false-positive onset and offset.

In this way, each segment was defined by data between the onset and offset time. We created the histogram of the data in each segment. As the shape of histogram largely fitted the normal distribution by visual observation, Gaussian parameters of every segment were extracted as the features for further classification. The features were identified by the following formula, where μ is mean of the distribution

and σ is standard deviation.

$$P(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-(x-\mu)^2/2\sigma^2}$$

4.2.2 Training

A large number of classification methods exist in the machine learning literature. SVM is a supervised learning method that attempts to find a hyper-plane separating the different classes of the training instances with the maximum error margin [21]. In other words, it tries to create a fence between the two classes, letting as few instances of a class to be on the wrong side of the fence as possible. Therefore it can be used to learn the optimised thresholds for differentiating pedalling techniques from the ground truth dataset.

A subset of our dataset was used to train the SVM classifier in order to classify the remaining data into quarter, half, three-quarters and full pedal. The cross-validation method was obeyed to evaluate the accuracies of our experiment, as this process was repeated as the training data and the data to be classified were rotated. Leave-one-group-out cross-validation was employed because of our small dataset. In this scheme, samples were grouped in terms of music excerpts. Each training set was thus constituted by all the samples except the ones related to a specific group. The number of pedalling instances in each music excerpt is listed in Table 1. A mean F-measure score of 0.93 was obtained from the cross-validation trials. Table 2 shows that SVM performs the best among common machine learning classification methods for our case using the scikit-learn library [16].

Table 1: Number of pedalling instances in the music excerpts from our dataset.

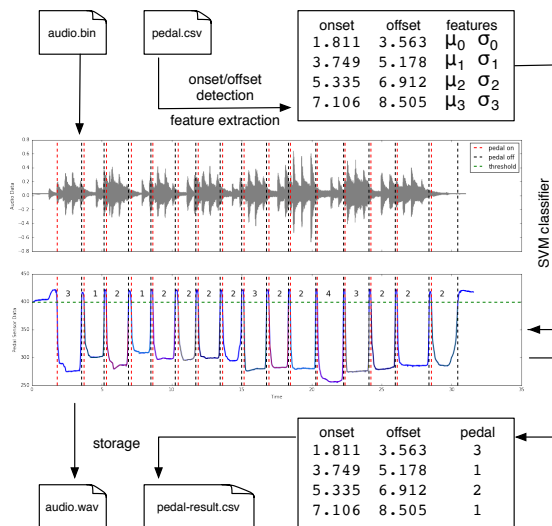
Music Excerpts	1/4	1/2	3/4	full pedal
Op.10 No.3	14	13	7	5
Op.23 No.1	7	17	8	29
Op.28 No.4	17	24	5	24
Op.28 No.6	9	27	5	17
Op.28 No.7	2	10	3	1
Op.28 No.15	7	34	4	22
Op.28 No.20	9	12	11	17
Op.66	6	21	10	11
Op.69 No.2	2	15	10	24
B.49	3	51	8	17
Sums	76	224	71	167

4.2.3 Testing

During the testing phase, the learned SVM classifier takes a new input sample that has not been seen before and assigns it an output label. Figure 2 illustrates the process of the testing phase in an intuitive way. The sensor data representing the pianist’s pedalling movement were processed as discussed in Section 4.2.1 in order to be segmented according to the detected pedalling onset and offset time. For each segment, the classifier received the Gaussian parameters (μ and σ) as features and outputted the label of the recognised pedalling technique. Label number 1 to 4 are referred to as the quarter, half, three-quarters and full pedal. We saved the pedal onset and offset time and the corresponding pedalling label to a file, which maintained synchronised time with the audio file and were used as the inputs of our visualisation application.

Table 2: Performance evaluation of different classification methods.

Methods	Micro F1	Macro F1	Precision	Recall
Decision Trees	0.91	0.81	0.84	0.83
Ada Boost	0.84	0.64	0.64	0.70
Random Forest	0.91	0.77	0.79	0.80
k-Nearest Neighbours	0.92	0.81	0.82	0.83
Gaussian Naive Bayes	0.91	0.78	0.85	0.80
Support Vector Machines	0.93	0.82	0.86	0.84

**Figure 2: Results from the testing phase.**

4.3 Visualisation

A score following Matlab implementation was employed as part of our visualisation application. This score following implementation can align a given musical score with an audio recording of a performance of the same piece. Asynchronies between the piano melody and the accompaniment were handled by a multi-dimensional variant of dynamic time warping (DTW) algorithm [22] in order to obtain better alignments.

In our case, the pedalling classification results were aligned with the audio recording. Hence they can also be presented synchronously in the score using the customised notations. Figure 3 displays the screen shot of our visualisation application. This graphical user interface (GUI) requires user to select a music score first. After importing the audio recording and the corresponding pedalling results of the same piece, they can be displayed by clicking the Play/Pause button. In the GUI, blue circles imply what notes in the score are being played according to the audio. Star means pedal onset while green square means offset. The more dark red and lower a star is, the deeper the sustain pedal was pressed.

5. CONCLUSIONS AND FUTURE WORKS

This paper presented Piano Pedaller, a new measurement system for classification and visualisation of piano pedalling techniques. It can be installed on any piano pedal which allows pedalling gesture and piano sound to be recorded in a non-intrusive environment. A SVM algorithm was employed as the classifier. Then the classification was done by firstly detecting the onset and offset time of pedalling and then labelling the gesture into quarter, half, three-quarters or full pedalling technique. The visualisation was achieved using a score following system. This aligns the musical score

to both the classification results of pedalling techniques and the audio recording of the same piece.

It has shown that the measurement system enables the piano pedalling gesture to be tracked accurately enough for SVM-based classification. Since different pianists have various understandings of partial pedal which could also be changed with the performance venue, the pianist needs to train the system beforehand in a concrete concert-like situation. How to develop a generalised software incorporating the training phase in order to classify the pedalling techniques in different contexts remains as a limitation in this study. In our future works, Piano Pedaller could be applied to the following scenarios:

- *Pedalling detection from the audio domain:* Automatic acquisition from audio recordings is necessary in special environments where installing sensors on instrument is not possible. Our measurement system can be used to capture the ground truth dataset for the study of pedalling techniques detection from the audio alone. The classification could contribute to this dataset by providing onset and offset time plus the category of a pedalling technique.
- *Real-time application:* The analysis is made offline so that our visualisation application allows player to review the pedalling techniques used in a recording. This could serve as a pedagogy application. If we consider how a technique is executed during the performance, a real-time application is needed. This could also be used to trigger other visual effects in the performance as pedalling itself is related to music phrases.

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7. REFERENCES

- [1] Piano bar. *Computer Music Journal*, 29(1):104–114, 2005.
- [2] M. Bernays and C. Traube. Investigating pianists’ individuality in the performance of five timbral nuances through patterns of articulation, touch, dynamics, and pedaling. *Individuality in music performance*, page 35, 2014.
- [3] W. Brent. The gesturally extended piano. In *Proceedings of the International Conference on New Interfaces for Musical Expression (NIME)*, 2012.
- [4] B. Caramiaux and A. Tanaka. Machine learning of musical gestures. In *Proceedings of the International Conference on New Interfaces for Musical Expression (NIME)*, pages 513–518, 2013.



Figure 3: Screen shot of the visualisation application.

- [5] N. Gillian and S. Nicolls. A gesturally controlled improvisation system for piano. In *Proceedings of the International Conference on Live Interfaces*, number 3, 2012.
- [6] W. Goebel, S. Dixon, G. De Poli, A. Friberg, R. Bresin, and G. Widmer. Sense in expressive music performance: Data acquisition, computational studies, and models. *Sound to sense-sense to sound: A state of the art in sound and music computing*, pages 195–242, 2008.
- [7] A. Hadjakos, E. Aitenbichler, and M. Mühlhäuser. The elbow piano: Sonification of piano playing movements. In *Proceedings of the International Conference on New Interfaces for Musical Expression (NIME)*, pages 285–288, 2008.
- [8] A. Hadjakos and M. Mühlhäuser. Analysis of piano playing movements spanning multiple touches. In *Proceedings of the International Conference on New Interfaces for Musical Expression (NIME)*, pages 335–338, 2010.
- [9] P. Le Huray. *Authenticity in performance: eighteenth-century case studies*. CUP Archive, 1990.
- [10] H. M. Lehtonen. *Analysis and parametric synthesis of the piano sound*. PhD thesis, Helsinki University of Technology, 2005.
- [11] H. M. Lehtonen, H. Penttinen, J. Rauhala, and V. Välimäki. Analysis and modeling of piano sustain-pedal effects. *The Journal of the Acoustical Society of America*, 122(3):1787–1797, 2007.
- [12] A. McPherson. Portable measurement and mapping of continuous piano gesture. In *Proceedings of the International Conference on New Interfaces for Musical Expression (NIME)*, pages 152–157, 2013.
- [13] A. McPherson and Y. Kim. Piano technique as a case study in expressive gestural interaction. In *Music and Human-Computer Interaction*, pages 123–138. Springer, 2013.
- [14] A. McPherson and V. Zappi. An environment for submillisecond-latency audio and sensor processing on beaglebone black. In *Proceedings of 138th International Audio Engineering Society (AES) Convention*. Audio Engineering Society, 2015.
- [15] K. Pandia, S. Ravindran, R. Cole, G. Kovacs, and L. Giovangrandi. Motion artifact cancellation to obtain heart sounds from a single chest-worn accelerometer. In *IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 590–593. IEEE, 2010.
- [16] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12:2825–2830, 2011.
- [17] W. H. Press, B. P. Flannery, S. A. Teukolsky, W. T. Vetterling, and P. B. Kramer. *Numerical recipes: the art of scientific computing*. AIP, 1987.
- [18] S. P. Rosenblum. Pedaling the piano: A brief survey from the eighteenth century to the present. *Performance Practice Review*, 6(2):8, 1993.
- [19] D. Rowland. *A history of pianoforte pedalling*. Cambridge University Press, 2004.
- [20] D. R. Sinn. *Playing Beyond the Notes: A Pianist's Guide to Musical Interpretation*. Oxford University Press, 2013.
- [21] A. J. Smola and B. Schölkopf. A tutorial on support vector regression. *Statistics and computing*, 14(3):199–222, 2004.
- [22] S. Wang, S. Ewert, and S. Dixon. Compensating for asynchronies between musical voices in score-performance alignment. In *IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 589–593. IEEE, 2015.
- [23] Q. Yang and G. Essl. Visual associations in augmented keyboard performance. In *Proceedings of the International Conference on New Interfaces for Musical Expression (NIME)*, 2013.
- [24] V. Zandt-Escobar, B. Caramiaux, A. Tanaka, et al. Piaf: A tool for augmented piano performance using gesture variation following. In *Proceedings of the International Conference on New Interfaces for Musical Expression (NIME)*, 2014.