# DETECTION OF MOTOR CHANGES IN VIOLIN PLAYING BY EMG SIGNALS

**Ling-Chi Hsu, Yu-Lin Wang, Yi-Ju Lin, Alvin W.Y. Su**
Department of CSIE, National Cheng-Kung University, Taiwan
t19897843@gmail.com;
daphne.yl.wang@gmail.com;
lyjca.cs96@g2.nctu.edu.tw;
alvinsu@mail.ncku.edu.tw

**Cheryl D. Metcalf**
Faculty of Health Sciences, University of Southampton, United Kingdom
c.d.metcalf@soton.ac.uk

## ABSTRACT

Playing a music instrument relies on the harmonious body movements. Motor sequences are trained to achieve the perfect performances in musicians. Thus, the information from audio signal is not enough to understand the sensorimotor programming in players. Recently, the investigation of muscular activities of players during performance has attracted our interests. In this work, we propose a multi-channel system that records the audio sounds and electromyography (EMG) signal simultaneously and also develop algorithms to analyze the music performance and discover its relation to player's motor sequences. The movement segment was first identified by the information of audio sounds, and the direction of violin bowing was detected by the EMG signal. Six features were introduced to reveal the variations of muscular activities during violin playing. With the additional information of the audio signal, the proposed work could efficiently extract the period and detect the direction of motor changes in violin bowing. Therefore, the proposed work could provide a better understanding of how players activate the muscles to organize the multi-joint movement during violin performance.

## 1. INTRODUCTION

For musicians, their motor skills must be honed by many hours of daily practice to maintain the performing quality. Motor sequences are trained to achieve the perfect performances. Playing a musical instrument relies on the harmonious coordination of body movements, arm and fingers. This is fundamental to understanding the neurophysiological mechanisms that underpin learning. It therefore becomes important to understand the sensorimotor programming in players. In the late 20th century, Harding et al. [1] directly measured the force between player's fingers and piano keys with different skill levels. Engel et al. [2] found there is an anticipatory change of sequential hand movements in pianists. Parlitz et al. [3] explored the dynamic pressures to analyze how pianists depressed the piano keys and hold them down during playing. The pressure measurement advances the evaluation of the keystroke in piano playing [4-5]. The use of muscle activity via electromyography (EMG) signals allows further investigation into the motor control sequences that produce the music. EMG is a technique which evaluates the electrical activity of the muscle by recording the electrical potentials when muscles generate an electrical voltage during activation, which results in a movement or coordinated action.

EMG is generally recorded in two protocols; invasive electromyography (IEMG) and surface electromyography (SEMG). IEMG is used to measure deep muscles and discrete positions using a fine-wire needle; however, it is not a preferable model for subjects due to the invasiveness and being less repetitive. Compared to IEMG, SEMG has the following characteristics: (1) it is non-invasive; (2) it provides global information; (3) it is comparatively simple and inexpensive; (4) it is applicable by non-medical personnel; and (5) it can be used over a longer time during work and sport activities [6]. Therefore, the SEMG is suitable for use within biomechanics and movement analysis, and was used in this paper.

For the analysis of musical performance, EMG has been used to evaluate behavioral changes of the fingers [7-8], upper limbs [9-10] shoulder [11-12] and wrist [13] in piano, violin, cello and drum players. The EMG method allows for differentiating the variations and reproducibility of muscular activities in individual players. Comparing the EMG activity between expert pianists and novice players [7-14] has also been studied.

There have been many approaches developed for segmentation of EMG signals [15]. Prior EMG segmentation techniques were mainly used to detect the time period for a certain muscle contraction, but we found that the potential variations from various muscles maybe different during a movement. It causes the conventional EMG segmentation to fail to extract the accurate timing of movement in instrument playing.

In this paper, the timing activation of the muscle group is assessed, and the changes in motor control of players during performance are investigated. We propose a system with the function of concurrently recording the audio signal and behavioral changes (EMG) while playing an instrument. This work is particularly focused on violin playing, which is considered difficult to segment with the soft onsets of the notes. The segment with body movements was first identified by the information of audio sounds. It is believed that if there is an audio signal, then there is a corresponding movement. Six features were then introduced to EMG signals to discover the variation of movements. This work identifies the individual movement segments, i.e. up-bowing and down-bowing, during violin playing. Thus, how motor systems operated in musicians and affected during performance could be explored using this methodology.

This paper is organized as follows. The multi-channel signal recording system and its experimental protocol are shown in section 2. In section 3, we introduce the proposed algorithms for segmenting the EMG signal with additional audio information. The experimental results are shown in section 4 and the conclusion and future work are given in section 5.

## 2. AUDIO SOUNDS AND BIOSIGNAL RECORDING SYSTEM

This work proposed a multi-channel signal recording system capable of recording audio and EMG signals concurrently. The system is illustrated in Figure 1 and comprises: (a) a signal pre-amplifier acquisition board, (b) an analog to digital signal processing unit, and (c) a host-system.

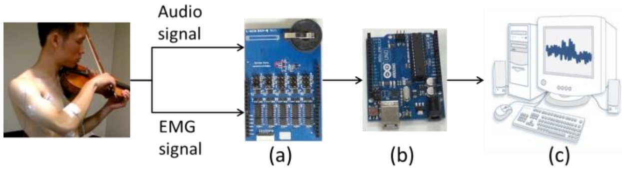


**Figure 1**. The proposed multi-channel recording system for recording audio signal and EMG concurrently.

The violin signal was recorded in a chamber and the microphone was placed 30cm from the player with a sampling rate of 44100Hz. With this real violin recording, the sound is supposedly embedded with the noise and the artifacts.

Furthermore, there is three subjects in the experiment database. The violinist play music and be recorded. Each participant was requested to press one string during playing. This experiment included two tasks for performance evaluation, and each task contained 10 movements. The movements for task#1 and task#2 are defined as follows.

Movements for task#1:

(1) Player presses the 2nd string then is idle for 2s (begin the bow at the frog).
(2) Pulls the bow from the frog to the tip for 4s (whole bow down).
(3) Pulls the whole bow up for 4s.

Movements for task#2:

(1) Player presses the 3rd string then is idle for 2s (begin the bow at the tip).
(2) Pulls the whole bow up for 4s.
(3) Pulls the whole bow down for 4s.

Two seconds resting time was given between the two consecutive movements.

The EMG sampling rate was 1000Hz. The electrodes attached on the surface of the player's skin as shown Figure 2. In this study, the direction of violin bowing, i.e. up-bowing and down-bowing, is detected by the corresponding muscle activity (EMG signal). The total of 8 muscles in the upper limb and body is measured in our system. Figure 3 shows the 8-channel EMG signals of up-bowing movement, and potential variations were shown in all channels when bowing. Three types of variations were observed and grouped:

(1) Channel#1 to Channel#6: it is seen that the trend of six channels is similar; additionally, the average noise floor between channel#3 and channel#6 are lower than others; finally, we choose channel#6 because the position is convenient to place the electrode.
(2) Channel#7: the channel involving the most noise.
(3) Channel#8: although it has more noise than Channel#1 to Channel#6, it is the important part when we have a whole-bowing movement.

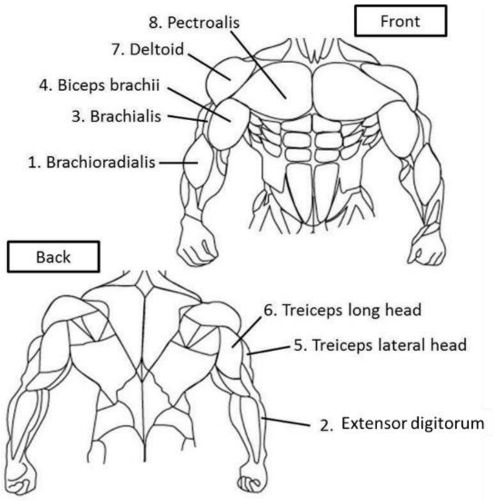


**Figure 2**. The placement of the electrodes attached on the player's skin [16, 17].

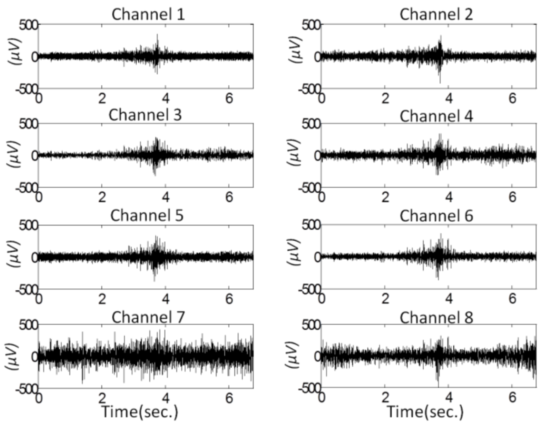


**Figure 3.** The 8-channel EMG signals of up-down bowing movements.

To reduce the computation and retain the variety of features, only channel#6 and channel#8 were thereafter used for further analysis. Figure 4 shows the EMG signals of channel#6 and channel#8 while during down-bowing.

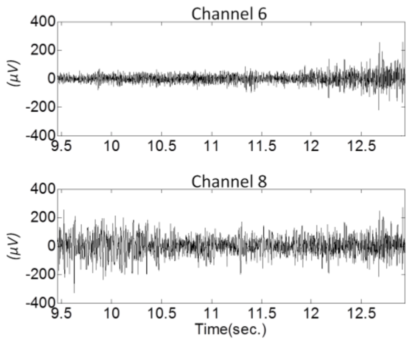


**Figure 4.** The EMG signals of triceps (channel#6) and pectoralis (channel#8) during down-bowing movements.

## 3. METHOD

The following section will introduce the proposed algorithm for detecting the bowing states during violin playing. The proposed system is capable of recording audio and EMG signals concurrently, and in this study a bowing state detection algorithm was developed, which was implemented the embedded system. The flowchart of the proposed method is shown in Figure 5.

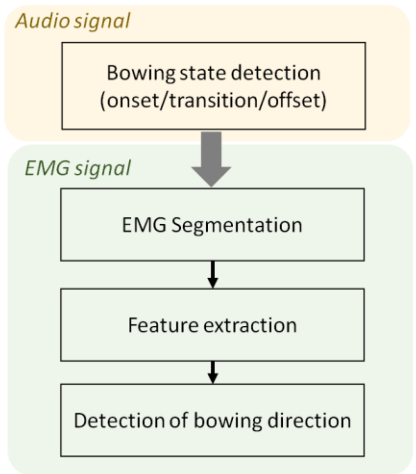


**Figure 5.** Flowchart of the proposed system.

The EMG signals were segmented according to the violin sounds. Then, six features were identified to detect the direction of bowing movements. For analyzing the audio signal, the window size of a frame is 2048 samples and the hop size 256 samples.

### 3.1 Onset/Transition/Offset detection

This section elaborates on the state detection of audio sounds. The states of audio sounds are defined as *Onset*, *Transition* and *Offset* in this study. The *Onset* is the beginning of bowing; the *Transition* is the timing when the next bowing movement occurred; the *Offset* is the end of the bowing; the *Sustain* is the duration of the note segment. Both frequency and spatial features were calculated and used as the inputs to our developed finite state machine (FSM). The diagram of our proposed FSM is illustrated in Figure 6. The output of FSM identifies the result of note detection and further used for EMG segmentation.

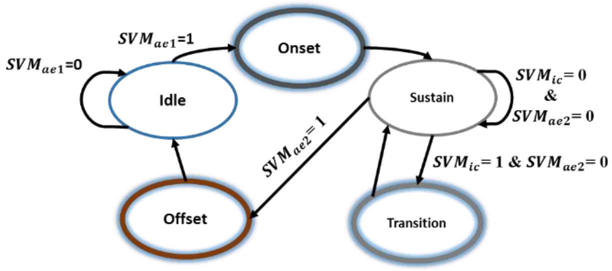


**Figure 6.** The state diagram of audio sounds.

The violin signal was analyzed both in frequency and time domains. For frequency analysis, the violin signal was first transformed by short time Fourier transform. The inverse correlation (IC) was then applied to calculate the possible note onset period. The inverse correlation (IC) coefficients are computed from the correlation coefficients of two consecutive discrete Fourier transform spectra [18]. A support vector machine (SVM), denoted as $SVM_{ic}$ (1), was applied for detecting the accurate timing of onset. SVM is a popular methodology, with high speed and simple implementation, for classification and regression analysis [19].

$$SVM_{ic} = \begin{cases} 0 & , \quad non-transition \\ 1 & , \quad transition \end{cases} \tag{1}$$

For spatial analysis, the amplitude envelop (AE) was used to detect the segment of the sound data. AE is evaluated as the maximum value of a frame. There are two similar classifiers, called $SVM_{ae1}$ (2) and $SVM_{ae2}$ (3). $SVM_{ae1}$ is used to identify the possible onsets and $SVM_{ae2}$ is used to identify the possible offsets.

$$SVM_{ae1} = \begin{cases} 0 & , \quad non-onset \\ 1 & , \quad onset \end{cases} \tag{2}$$

$$SVM_{ae2} = \begin{cases} 0 & , \quad non-offset \\ 1 & , \quad offset \end{cases} \tag{3}$$

Figure 7 shows (a) a segment of audio sounds with one sequence of down-bowing and up-bowing, while Figure 7(b) and (c) display the results of IC and AE, respectively.

During the bowing state, the IC value is extremely small when compared to the results of the non-bowing state. IC seems to be a good index to identify the state of whether the violin is being played, or not. However, it can be seen that a time deviation is introduced if the system simply applies a hard threshold, e.g. 0.3. Alternatively, the AE value becomes larger at the playing state. But the issue of time deviation is also present in this feature, if a hard threshold is applied.

After calculating the IC and AE values, their variation is considered as one set of input data for SVM. The time period of each data is 100ms. Therefore, $SVM_{ic}$, $SVM_{ae1}$ and $SVM_{ae2}$ are designed to detect the most plausible timing of onset, transition and offset.

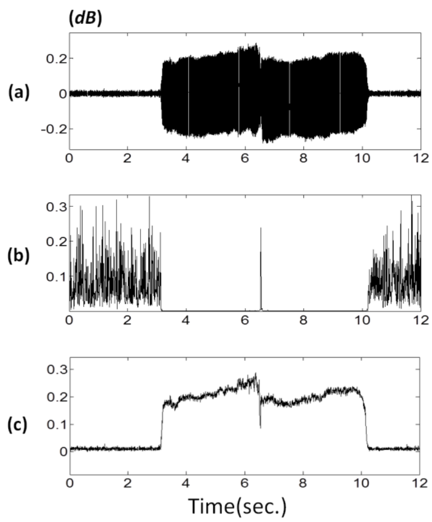


**Figure 7.** (a) The audio sounds of down-bowing and up-bowing; (b) the results of IC; (c) the results of AE

### 3.2 Detection of bowing direction

In each movement, there are one onset, one offset, and several transitions. However, the total number of transitions will differ from the number of notes. After detection of the bowing state is completed, the duration between onset and offset is applied for segmenting the EMG signal of triceps (channel#6) and pectroalis (channel#8). For each note duration, there are three cases:

(1)The duration from the onset to the first transition.

(2)The duration from the current transition to the next transition.

(3)The duration from the last transition of the offset.

This note duration extracted from the audio sound is called an active frame and the active frames are variant lengths from each other. The segment extracted by the audio sounds is called an *active frame* and the active frames are variant lengths from each other.

For each active frame, six features in [20] were applied to calculate the variations of EMG signal while bowing. The features are:

- Mean absolute value (MAV)
- Mean absolute value slope (MAVS)
- Zero crossings (ZC)
- Slope sign changes (SSC)
- Waveform length (WL)
- Correlation variation (CV)

Here, the active frame is experimentally divided into 20 segments for calculating MAV and WL, thus each active frame has 20 values of MAV and WL. For CV, we calculate the auto-correlation and cross-correlation of channel#6 and channel#8, and therefore there are 3 values of CV for each active frame. Table 1 lists the number of each feature for each channel.

**Table 1.** The number of each feature per channel

| **Feature** | MAV | MAVS | ZC | SSC | WL |
|---|---|---|---|---|---|
| **Number** | 20 | 19 | 1 | 1 | 20 |

A more detailed description of those applied features could be found in [20]. Figure 8 displays the triceps EMG signal of one active frame (8s ~ 16s) and the results calculated by MAV, MAVS, ZC, SSC and WL. It can be seen that variations are exhibited for 6 features in violin playing with a down-up bowing movement.

The detection of bowing direction is also determined by a SVM classifier which is denoted as $SVM_{dir}$ (3). For $SVM_{dir}$, a total of 125 inputs are used (61 inputs for channel#6 and channel#8 each, plus 3 values of CV) and it identifies whether the active EMG frame is in the up-bowing or down-bowing state.

$$SVM_{dir} = \begin{cases} 0 \quad , \quad Up-bowing \\ 1 \quad , \quad Down-bowing \end{cases} \tag{3}$$

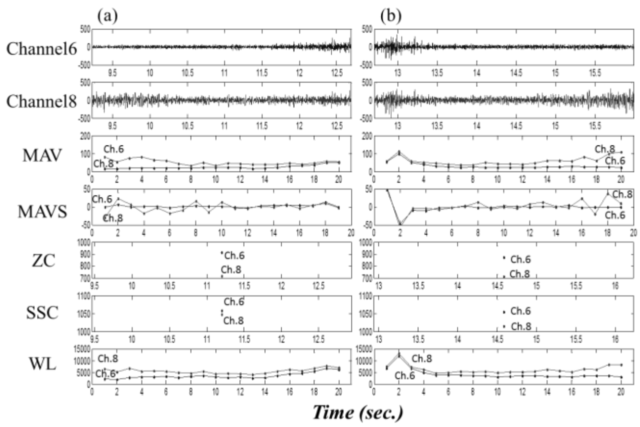


**Figure 8.** One down-up bowing movement and its six features: (a) the down-bowing movement, (b) the up-bowing movement.

### 3.3 Performance evaluation

In our experiment, 10-fold cross-validation is used for $SVM_{ic}$, $SVM_{ae}$ and $SVM_{dir}$, and the performance evaluation calculates the accuracy (4), precision (5), recall (6) and F-score (7) of each detecting function.

$$\text{Accuracy} = \frac{\textbf{True Positive}+\textbf{True}\ Negative}{\textbf{Positive}+Negative}; \tag{4}$$

$$\text{Precision} = \frac{True\ Positivze}{True\ Positive+False\ Positive}; \tag{5}$$

$$\text{Recall} = \frac{True\ Positive}{True\ Positive+False\ Negative}; \tag{6}$$

$$\text{F-score} = \frac{2\cdot Precision\cdot Recall}{Precision+Recall}; \tag{7}$$

The true positive means it correctly detected the movement; the false positive is a falsely detected movement; and the false negative is a missed detection.

## 4. EXPERIMENTAL RESULTS

In this section, the efficiency of the proposed SVMs is observed. An example of the proposed EMG segmentation is then compared to the prior work [15]. Finally, the averaged and overall simulation results are given.

### 4.1 The performance of SVM classifications

To illustrate both the proposed IC and AE effectively identify the sound states of onset and offset, respectively, Figure 9 shows the trend of IC and AE values in one down-up bowing movement by using the classification results for $SVM_{ic}$ and $SVM_{ae1}$ and $SVM_{ae2}$. Table 2 shows that, with the given FSM, the detection rate of onsets, transitions and offsets are 90%, 100%, 100%, respectively.

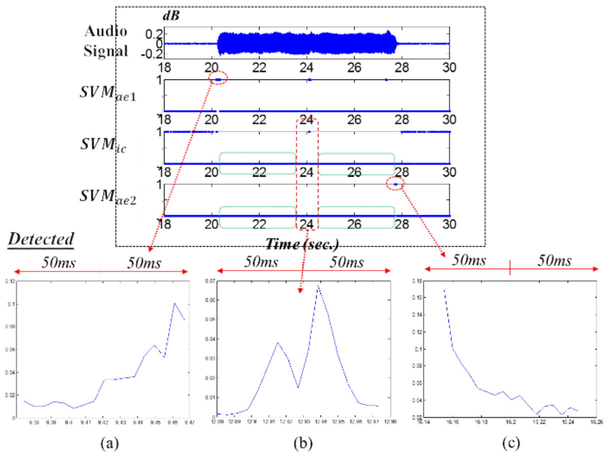


**Figure 9.** The results of 3 classifiers: (a) onsets, (b) transitions, (c) offsets.

**Table 2.** The detection results of the bowing states with the given FSM.

| | Onset | Transition | Offset |
|---|---|---|---|
| **Accuracy** | 90.00% | 100% | 100% |
| **Precision** | 90.00% | 100% | 100% |
| **Recall** | 90.00% | 100% | 100% |
| **F-score** | 90.00% | 100% | 100% |

Figure 10 shows the distribution of active EMG frames during up-bowing and down-bowing states, and it displays the distribution of MAV, MAVS and WL. The $SVM_{dir}$ classifies the data with 85% accuracy.

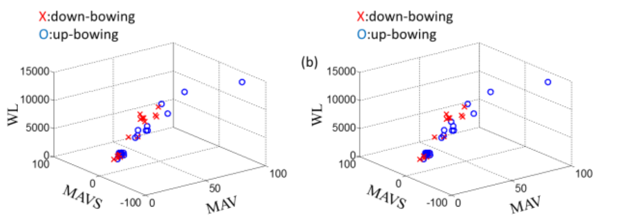


**Figure 10.** (a) The original distribution of up-bowing and down-bowing EMG frames; (b) the results of $SVM_{dir}$ classification.

### 4.2 EMG segmentation

The results of EMG segmentation and its comparison to [15] are both illustrated in Figure 11. Figure 11 shows the violin signal of task#1 with three movements. Figure 11 (b) and (c) are the EMG segmentations of our proposed method and [15], respectively. Channel#6 is used in this example to illustrate a sample output. It is believed that if there is an audio signal, then there is a corresponding movement. It can be seen that the results segmented by [15], without the additional information of the audio signal, could not precisely identify the segment of movements during bowing. However, the proposed method is based on the information from audio signals and clearly identifies the segment of behavioral changes during violin playing.

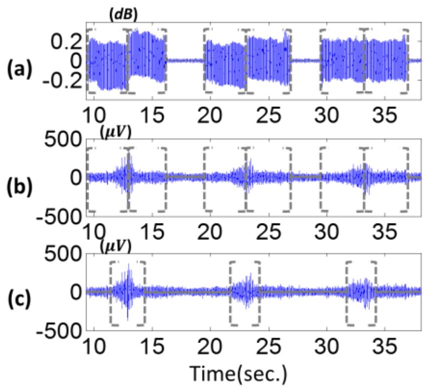


**Figure 11.** (a) The violin signal; (b) the proposed EMG segmentations; (c) the EMG segmentations of [15].

### 4.3 The simulation results

The detection result of violin bowing direction was given in Table 3 where accuracy, precision, recall and F-score are presented.

**Table 3.** The detection results of the bowing direction: (1) the detection results of ground truths of active frames; (2) the detection results of extracted active frames.

| | (1) | (2) |
|---|---|---|
| **Accuracy** | 85% | 87.5% |
| **Precision** | 76.92% | 82.61% |
| **Recall** | 100% | 95% |
| **F-score** | 86.96% | 88.37% |

The average detection results were shown to have excellent performance with an accuracy of 85%~87.5%. The results show that the proposed method efficiently identifies the bowing direction in violin playing.

## 5. CONCLUSION AND FUTURE WORK

The proposed biomechanical system for recording the audio sounds and EMG signals during playing an instrument was developed. The proposed method not only extracts the segment during movement and detects the moving direction of bowing, but with the additional information of violin sounds, changes in muscle activity as an element of motor control, could be efficiently detected when compared to the prior EMG segmentation (without any sound information). To the authors' knowledge, this is the first study which proposes such concept.

Future work will improve the detection rate of onset, transition and offset to extract the period of an active frame more precisely. The detection of the bowing direction will be also improved. Furthermore, the relationship between the musical sounds and the muscular activities of players in musical performance will be observed and analyzed. By measuring the music and the player's muscular activity, better insights can be made into the neurophysiological control during musical performances and may even prevent players from the injuries as greater insights into these mechanisms are made.

## 6. REFERENCES


[1] DC. Harding, KD. Brandt, and BM. Hillberry: "Minimization of finger joint forces and tendon tensions in pianists," *Med. Probl. Perform Art* pp.103-104, 1989.

[2] KC. Engel, M. Flanders, and JF. Soechting: "Anticipatory and sequential motor control in piano playing," *Exp Brain Res*. pp. 189-199, 1997.

[3] D. Parlitz, T. Peschel, and E. Altenmuller: "Assessment of dynamic finger forces in pianists: Effects of training and expertise," *J. Biomech.* pp.1063-1067, 1998.

[4] H. Kinoshita , S. Furuya , T. Aoki, and E. Altenmüller E.: "Loudness control in pianists as exemplified in keystroke force measurements on different touches," *J Acoust Soc Am.* pp. 2959-69, 2007.

[5] AE. Minetti, LP. Ardigò, and T. McKee: "Keystroke dynamics and timing: Accuracy, precision and difference between hands in pianist's performance," *J Biomech*. pp. 3738-43, 2007.

[6] R. Merletti and P. Parker: Electromyography: physiology, engineering, and noninvasive applications, *Wiley-IEEE Press*, 2004.

[7] C.-J. Lai, R.-C. Chan, and T.-F. Yang *et al*.: "EMG changes during graded isometric exercise in pianists: comparison with non-musicians," *Journal of the Chinese Medical Association*, vol. 71, no. 11, pp. 571-575, 2008.

[8] M. Candidi, L. M. Sacheli, and I. Mega *et al*.: "Somatotopic mapping of piano fingering errors in sensorimotor experts: TMS studies in pianists and visually trained musically naïves," *Cerebral Cortex*, vol. 24, no. 2, pp. 435-443, 2014.

[9] S. Furuya, T. Aoki, and H. Nakahara *et al*.: "Individual differences in the biomechanical effect of loudness and tempo on upper-limb movements during repetitive piano keystrokes," *Human movement science*, vol. 31, no. 1, pp. 26-39, 2012.

[10] D. L. Rickert and M. Halaki, K. A. Ginn *et al*.: "The use of fine-wire EMG to investigate shoulder muscle recruitment patterns during cello bowing: The results of a pilot study," *Journal of Electromyography and Kinesiology*, vol. 23, no. 6, pp. 1261-1268, 2013.

[11] A. Fjellman-Wiklund and H. Grip, J. S. Karlsson *et al*.: "EMG trapezius muscle activity pattern in string players: Part I—is there variability in the playing technique?," *International journal of industrial ergonomics*, vol. 33, no. 4, pp. 347-356, 2004.

[12] J. G. Bloemsaat, R. G. Meulenbroek, and G. P. Van Galen: "Differential effects of mental load on proximal and distal arm muscle activity," *Experimental brain research*, vol. 167, no. 4, pp. 622-634, 2005.

[13] S. Fujii and T. Moritani: "Spike shape analysis of surface electromyographic activity in wrist flexor and extensor muscles of the world's fastest drummer," *Neuroscience letters*, vol. 514, no. 2, pp. 185-188, 2012.

[14] S. Furuya and H. Kinoshita: "Organization of the upper limb movement for piano key-depression differs between expert pianists and novice players," *Experimental brain research*, vol. 185, no. 4, pp. 581-593, 2008.

[15] P. Mazurkiewicz, "Automatic Segmentation of EMG Signals Based on Wavelet Representation," Advances in Soft Computing Volume 45, 2007, pp 589-595

[16] Bodybuilding is lifestyle! "Chest - Bodybuilding is lifstyle!"http://www.bodybuildingislifestyle.com/chest/.

[17] Bodybuilding is lifestyle! "Chest - Bodybuilding is lifestyle!" http://www.bodybuildingislifestyle.com/hamstrings/.

[18] WJJ. Boo, Y. Wang, and A. Loscos, "A violin music transcriber for personalized learning," pp 2081-2084, *IEEE International Conference on Multimedia and Expo*, 2006.

[19] BE. Boser, IM. Guyon and VN. Vapnik: "A training algorithm for optimal margin classifiers," In Fifth Annual Workshop on Computational Learning Theory, ACM 1992.

[20] AJ. Andrews: "Finger movement classification using forearm EMG signals," *M. Sc. dissertation, Queen's University*, Kingston, ON, Canada, 2008.