New Sensors and Pattern Recognition Techniques for String Instruments

Tobias Großhauser Ulf Großekathöfer Thomas Hermann
Center of Excellence in Cognitive Interaction Technology
Ambient Intelligence Lab
Bielefeld University, Bielefeld, Germany
{tgrossha|ugrossek|thermann}@techfak.uni-bielefeld.de

ABSTRACT

Pressure, motion, and gesture are important parameters in musical instrument playing. Pressure sensing allows to interpret complex hidden forces, which appear during playing a musical instrument. The combination of our new sensor setup with pattern recognition techniques like the lately developed ordered means models allows fast and precise recognition of highly skilled playing techniques. This includes left and right hand analysis as well as a combination of both. In this paper we show bow position recognition for string instruments by means of support vector regression machines on the right hand finger pressure, as well as bowing recognition and inaccurate playing detection with ordered means models. We also introduce a new left hand and chin pressure sensing method for coordination and position change analysis. Our methods in combination with our audio, video, and gesture recording software can be used for teaching and exercising. Especially studies of complex movements and finger force distribution changes can benefit from such an approach. Practical applications include the recognition of inaccuracy, cramping, or malposition, and, last but not least, the development of augmented instruments and new playing techniques.

Keywords

Sensor, Strings, Pressure, Ordered Means Models, Left Hand, Right Hand, Violin

1. INTRODUCTION

Over the past years many audio and gesture parameters have already been investigated with sensor data, audio and video analysis in the fields of exercising, teaching, and performing of musical instruments.

In numerous recent papers and articles of e.g. Rasamimanana et al. [14], Maestre [11], and in his thesis about bowing gestures [10] interesting approaches about gesture recognition and especially bowing gestures have been developed and realized. The mainly used measuring methods in case of pressure are one or more foil strains placed in the middle of the bow, introduced by Young [16]. The other pressure measure method is described by Demoucron et al. [4] where the overall pressure of the bow hair is measured near the frog. This method reduces the length of the bow hair and can damage the varnish of the violin. Beside the first finger pressure measurement of the commercially available K-Bow from Keith A. McMillen, which is a complete bow and does not allow to use the existing bow of the violinist, the developments of IRCAM, also partly used by the before mentioned authors are state of the art. This means radio frequency transmission, gyroscopes, acceleration, and other sensors, integrated into smallest PCBs fixed on the frog beginning with the work of Bevilaqua et al. [1]. These are just the most recent developments – the "history of violin sensing" goes back for many more years and approaches. All video or VICON based systems, e.g. the one described by Ng [12] were not mentioned here and would extend the list. The systems allow sensor-based motion and gesture tracking in 3D, overall bow pressure and many more parameters.

Figure 1: Picture of the bow mounted pressure sensors, after ca. 3000 played bowing samples.

With the method described here, a further development of Grosshauser's approach [7] is made, where every finger is measured and we can draw conclusions to cramping, faults, bow position, and different types of bow strokes, just to name a few. In general, the fixation of the sensors is easy. Furthermore, our sensor concept enables wrist mounting, which some violinists prefer.

The sensing technologies we use in this study extend the approved practices, e.g. by measuring the pressure of every finger. In addition, we apply advanced machine learning techniques to the sensor data, namely *support vector regression machines* (SVRs) and *ordered means models* (OMMs). As a basic technology we use a high sensitive pressure sensor. Since new and easy-to-build pressure sensors, such as the paper FSRs introduced by Koehly et al. [9], are very flexible and cheap. It is possible to independently measure the pressure of each finger of the right and left hands. For further analysis of the pressure data, we implement a recording and visualization program. We accomplish experiments to explore bow position recognition as well as classification of bowing types. This includes different tempi and inaccurate bowings with too much or less pressure, or a wrong bow angle. Furthermore, we give prospects of practical use cases for teaching and exercising. Last but not least, we discuss new playing techniques, which are enabled by these unobtrusive, easy-to-use sensor setup.

2. SENSOR SETUP AND MEASUREMENTS

The used sensing method was introduced at NIME08 by Grosshauser [7]. First results of pressure and position measurements were shown as well as applications for teaching and first composition examples.

In this study, we apply several improvements, including a left hand sensor, a goniometer and the application of advanced data mining methods.

Each sensor is connected via cable directly with a wrist mounted PCB board equipped with AD-converters, an Atmega 328 IC and a small Bluetooth module, or in a different configuration with a small module on the frog of the bow, similar to [1], with the same technical features as mentioned before. The modular setup allows a flexible number of sensors to be fixed on the bow or violin, depending on the needs of the student, teacher, or performer. The connector box can also be worn on a belt. Data transmission is possible either to a computer via Bluetooth or directly to synthesizers or other modules via OSC or MIDI. The data are recorded with a self developed data, audio and video recording, analysing and playback software written mainly in Java.

2.1 Measurement and Recording

Like mentioned before, we fixed FSR sensor foils to the frog of the bow at the contact point between the fingers and the bow (Fig. 1). One is mounted at the contact point of the thumb, forefinger and little finger, another one at the ring finger and middle finger, combined.

The relations of the pressure of each finger and especially the changes of it during one bow stroke and partly the bow position with the goniometer is measured and recorded. The collected data then are transmitted to the PC and visualized and recorded in real-time with our software (data plot see Fig. 2). Playback in slow motion is possible, allowing precise visual analysis.

Pressure Sensors

The dimension of the basic sensors we use are now between 2x2x0.3mm and 5x5x0.3mm, but any dimension is possible. Beginners need larger sensor dimensions, since the local variation of their fingers during playing is larger. It weights only few gram and does not affect the motion of the musicians. The heaviest part of the sensors is indeed the thin copper wire between the sensor and the ADC/IC/Bluetooth board.

Goniometers

For our first experiment we used a goniometer. This is an instrument which measures an axis and range of motion, or the angle or rotation of an object precisely about the attached axis between two connected arms or small sticks.

Our self made goniometers are equipped with a potentiometer and used for joint angle measurement. This is a very precise and cheap sensor, easy to fix and install. It can be mounted directly on the body or into the clothing, depending on how precise the measurement has to be. In our case, the goniometers are fixed to the body and used to learn the correlation between bow position and pressure data and between ellbow and wrist angles in left hand measurements (see sec. 2.1.3).

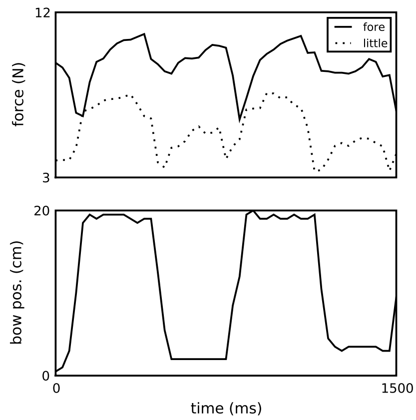

Figure 2: Plot of pressure of fore- and little finger and bow position, Martele up- and down-bow strokes.

2.1.1 Calibration

Although for all our experiments only the relationship of the pressure between the fingers is considered, we did a calibration to get an idea of the absolute pressure values in Newton. The pressures directly below the fingers get quite high, compared to the total force on the top of the bow, e.g. during a forte stroke, 1 N at the tip means up to 12 N on the forefinger on the frog.

We calibrated the sensors with two PCE-LSM2000 weighing machines, directly connected to the computer over RS232. We placed the weighing machines under the top and the frog of the bow and pushed each sensor several times. We estimated the absolute weight values by recording the values of the weighing machines and the pressure values of the sensors simultaneously and computing the linear correlation of both. We did a first run with defined weights on each sensor, a second one with constant weight change from zero to 2 kg in a CNC machine, and a last one with constantly changing finger pushes. In all three cases we achieved similarly correlated results.

2.1.2 Right Hand Sensing

We recorded different up- and down bowings and defined inaccurate and so-called "wrong bowings" in the traditional way of violin playing and teaching. The bowing types are Martele, Detache and Spiccato in different tempi.

The inaccurate examples were (i) wrong angle with more or less than 90°between bow and the strings, and (ii) too much or less pressure in combination with too long or short pressure. Depending to different playing techniques, wrong pressure distribution and inaccurate pressure changes before and during the stroke were recorded. Each case was conducted at least 200 times. In Fig. 2 a typical measurement of a Martele stroke is shown. The lower square-edged line is the bow position, the upper graphs depict the pressure of the fore- and little finger. The figure shows the preparation, execution, and wrap-up phases of four strokes. The distinction of up- and down-bow is evident. Also, the pressure change of the fore to the small finger and the different distribution between up- and down-bows can be seen.

Our first sensor setup was a goniometer on the right arm in addition to the pressure sensors to get the bow position. The clear correlations between the pressure and the goniometer data allowed us to reduce the setup and derive the bow position information without the goniometer (see

Figure 3: Picture of the violin mounted pressure sensors.

Fig. 5 and sec. 3.1).

Some considerations for the experiments and the classifications are the following:

1. **Distribution of the pressure:** Each type of bowings and playing techniques demands a different distribution of pressure between the fingers. E.g. Carl Flesch [5] emphases in his violin methodology a higher rotation of the hand, which results in more pressure between forefinger and thumb. Other violin schools, like the one of Ulf Klausenitzer, which is based on the ideas of Henrik Szering and Leonid Kogan, prefer a more flat hand. This leads to a more equal distribution of the pressure between all fingers. The different playing techniques are usually hard to explain and to train, and here our visualization and classification of the pressure data supports teaching and every-day exercising.

2. **Inaccurate execution recognition:** The used classification methods allow recognition of inaccurate playing. After training the system with good and defined inaccurate examples, certain faults like wrong angle, too much or too less pressure is recognized (see Sec. 4).

2.1.3 *Left Hand Sensing*

Beside left hand finger position sensing, which we are not interested in our left/right hand synchronisation and left hand pressures itself, left hand sensing for string instruments is underrepresented compared to right hand research. A recent article from Kinoshita et al. [8] shows one possibility to measure the left hand finger pressure at different volumes, tempi, and bowings on one single position on the fingerboard. In our case we can play a whole tune naturally and record the left and right hand parameters simultaneously. This means, finger pressure compared to bowings, speed, volume, and with different types of vibrato and double stops.

In this study, pressure sensors are fixed on the chin rest and on the neck of the violin, where thumb and the side of the first finger are in contact (see Fig. 4).

The executed task is to perform several scales with position shifts. The recording of position shifts shows the coordinated reduction of the finger pressure, here of the thumb and of one of the fingers 1-4, the increase of the chin pressure during the shifting phase and the increase of the pressure of the new position (see Fig. 4). These data allow a precise analysis, especially the timing between finger and chin rest, which is one of the most complex movements to learn and execute for beginners and to optimize for advanced students. Several teaching scenarios were recorded in the master violin class of Prof. Klausenitzer at the University of Nuernberg with live sensor based motion capturing and

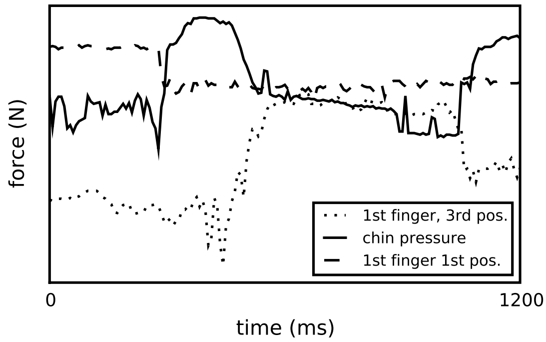

Figure 4: Transition between first and third position.

analysis. Advanced setups consists of additional chin rest pressure and left and right elbow, wrist, and shoulder measurements.

3. EXPERIMENTS

For the purpose of evaluation of the proposed system, we chose an experimental setup for investigation of the following questions:

1. Is it possible to predict the bow position by the means of the data from the pressure sensors?

2. Can the data from the pressure sensors be used to classify bowings and if so, to what accuracy?

3. Is it possible to detect inaccurate bowing executions by the data form the pressure sensors?

To address the first issue, we evaluated the recorded data with a standard framework for regression analysis, the so-called support vector regression machines. For analysis of the second and third question, we implemented an evaluation scheme for classification that is based on ordered means models.

We used data recorded from one subject who is a professional violinist. The subject participated in several recording sessions that took place during one week in our laboratory. The recording setup was simple: the sensors were attached to the subject's bow as described in section 2. The data were recorded by a standard laptop computer connected to the sensor board via Bluetooth. The required playing techniques were presented to the subject by oral instruction and, additionally, in musical notation. The recognition works independent of playing speed and without fixed tempo metronome pre-settings.

3.1 Bow Position Prediction

To obtain first insights about the recorded data, we performed an experiment in which we investigated whether the bow position can be predicted by only using the data from the pressure sensors. More formal, we estimated a function $f(\mathbf{o}_t) = b_t$ that maps the 4-dimensional pressure sensor vector $\mathbf{o}_t$ on a scalar b_t, corresponding to the bow position as given by the goniometer at time t.

The task of estimating a continuous function $f(.)$ is known as *(non-linear) regression analysis*, and there is a large body of techniques for modeling such a function $f(.)$ with a set of observations. We adopted a regression technique that is

identifier	run	number of examples
correct executions:		
MCS	martele slow	206
MCF	martele fast	198
DCS	detache slow	196
DCF	detache fast	156
SCS	spiccato slow	207
SCF	spiccato fast	192
inaccurate executions:		
MIA>90	martele angle >90	170
MIA<90	martele angle <90	203
MIP+	martele pressure+	133
MIP−	martele pressure−	206
DIA>90	detache angle >90	214
DIA<90	detache angle <90	206

Table 1: This table shows the number examples.

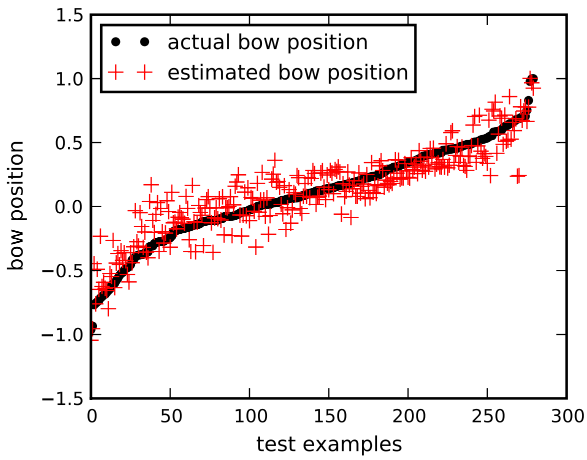

Figure 5: This figure shows the actual and predicted bow positions depending on the pressure measurements. Note that the bow position is normalized to the interval $[-1, 1]$.

based on the widely-used support vector machines (SVM) [2], the so-called support vector regression machines (SVR). In general, SVM are are known to be robust and reliable and, therefore they provide an ideal ad-hoc method for rapid evaluation of unknown data. There are various free implementations of SVMs and SVRs available on the internet. In this study, we use LIBSVM [3]. An introduction to SVR and algorithmic details can be found in Smola et al. [15].

We applied the following procedure to the data set: (i) We normalized all features to the interval $[-1, 1]$, (ii) we partitioned the data into training and test data sets of almost equal sizes, (iii) we used the training data set to validate the hyperparameters of the SVR by the means of 5-fold cross validation, (iv) we tested the resulting non-linear regression function with the dedicated test data set.

3.2 Bowing Classifications

In order to prepare the captured data for classification, we used the sensor data from the goniometer for stroke detection. Therefore, we parted the continuous data stream from the goniometer into fragments, each ranging from a local maximum to the nearest subsequent local minimum and vice versa. From this fragments, we only used the data of the pressure sensors for the classification experiments. Note that we did not distinguish between up-bows and down-bows in this scenario. Table 1 gives an brief overview of the data collected in this process.

For classification we used OMMs [6], a new approach to machine learning of time-series and sequences. OMMs can be described as rigorously reduced versions of the well-known and widely-used hidden Markov models (HMMs) [13]. While achieving similar generalization properties, OMMs provide a high level of robustness in terms of fragmented or insufficient data and, additionally, need less computational power.

Similar to HMMs, an OMM Ω can be characterized as a generative state-space model that emits a sequence of observation vectors $O = \mathbf{o}_1, \ldots, \mathbf{o}_T$, $\mathbf{o}_t \in \mathbb{R}^d$ out of K hidden states. In contrast to HMMs, OMMs establish some restrictions: (i) OMMs are defined without any transition probabilities. Instead, each valid path $\mathbf{q} = q_1, \ldots, q_T$ through the model, i.e. each valid combination of states, is equally likely. (ii) The emissions of each state are modeled as probability distributions $b_k(\mathbf{o}_t)$ and assumed to be Gaussian with $b_k(\mathbf{o}_t) = \mathcal{N}(\mathbf{o}_t; \boldsymbol{\mu}_k, \sigma)$. The standard deviation σ is identically in all states and used as a global hyperparameter. (iii) The model topology of OMMs is a left-to-right topology where only self transitions and transitions to subsequent states are allowed. Applying these restrictions, the only parameters left are the location parameters of the emission densities $\boldsymbol{\mu}_k$. Therefore, an OMM is completely defined by a linear array of reference vectors $\Omega = [\boldsymbol{\mu}_1 \ldots \boldsymbol{\mu}_K]$.

To learn the model parameters $\boldsymbol{\mu}_k$ from a set of N example sequences $\mathbf{O} = \{O^1, \ldots, O^N\}$, the log-likelihood

$$\mathcal{L} = \sum_{i=1}^{N} \ln p(O^i|\Omega) \tag{1}$$

is maximized with respect to the mean vectors $\boldsymbol{\mu}_k$.

Since this optimization problem has to be solved iteratively, the training process of such OMMs first computes the *responsibilities*

$$r_{kt}^i = \frac{p(O^i, q_t = k|\Omega)}{p(O^i|\Omega)} \quad \text{(E-step)} \tag{2}$$

by the means of dynamic programming and then re-estimates the model parameters $\boldsymbol{\mu}_k$ with

$$\boldsymbol{\mu}_k = \frac{\sum_{i=1}^{N}\sum_{t=1}^{T} r_{kt}^i \cdot \mathbf{o}_t^i}{\sum_{i=1}^{N}\sum_{t=1}^{T} r_{kt}^i} \quad \text{(M-step).} \tag{3}$$

This procedure is repeated until convergence.

To use OMMs for classification in a maximum likelihood framework, one model Ω_i is trained for each class i. An unknown sequence O then is assigned to the class $k = \arg\max_i p(O|\Omega_i)$, whose model yields the highest posterior probability. A more detailed introduction to OMMs and algorithmic details can be found in Großekathöfer et al. [6].

According to the collected data, we established various classification tasks with different class sets:

(A) **"bowings slow":** Martele vs. Detache vs. Spiccato with slow stroke frequency ($\approx$ 1Hz),

(B) **"bowings fast":** Martele vs. Detache vs. Spiccato with fast stroke frequency ($\approx$ 2Hz),

(C) **"detache angle":** correct Detache strokes vs. incorrect Detache strokes with an angle lower then 90°vs. incorrect Detache strokes with an angle above 90°,

(D) "martele angle": correct Martele strokes vs. incorrect Martele strokes with an angle lower then 90° vs. incorrect Martele strokes with an angle above 90°,

(E) "martele pressure": correct Martele strokes vs. incorrect Martele strokes with to much pressure vs. Martele strokes with not enough pressure.

The class sets (A) and (B) concern the general separability of bowings, whereas class sets (C), (D), and (E) are related to the question of detecting inaccurate bowing executions.

We applied an uniform procedure to all class sets: Firstly, we randomly partitioned all available data into equally sized training and test sets. The resulting training and test sets then were normalized to zero-mean and unit variance according to the training examples. Afterwards, we estimated appropriate hyperparameters for each method by means of 5-fold cross validation on the training data. In this process, we chose equal values for the number of OMM states K and the global standard deviation σ in all experiments with $K \in \{2, 4, \ldots, 20\}$ and $\sigma \in \{2.0, 1.6, 1.28, 1.02, 0.81, 0.65, 0.52, 0.41, 0.33, 0.26\}$. Subsequently, we took the best hyperparameters found to train OMM classifiers with the complete training data set. To obtain the test set error rate, we applied the resulting classifiers to the dedicated test sets. This procedure was repeated 100 times for each class set to enable simple statistics on the achieved error rates.

4. RESULTS AND DISSCUSION

The results of the bow position prediction reveals a mean square error $MSE = 0.021$ for the dedicated test data. Taking the normalization into account, this implies a deviation of $\approx 10\%$ between the estimated and the actual bow position. Figure 5 shows in detail the deviation for each test data point. As a consequence, this findings indicates that the goniometer sensor may be non-relevant in the described setting: It is possible to derive the bow position from the pressure sensors and, therefore, remove the goniometer from the setup.

The results of the bowings classification experiments are summarized in Table 2 and Figure 6. As a main result, OMMs are able to correctly classify examples from all class sets with high accuracy. For the 100 runs of class sets (A) and (B), which are related to bowing detections, we found a mean error rate of $\approx 2\%$ and $\approx 3\%$, respectively, with a standard deviation of $\approx 1\%$ in both cases. OMMs provide very stable recognition rates, and there seems to be almost no dependency on the execution speed.

Additionally, OMMs detect incorrect bowing execution with reasonable accuracy. For the class sets (C) and (D), which are related to incorrect bowing angles, the classifiers reached a mean error rate of $\approx 13\%$ and $\approx 9\%$ with a standard deviation of $\approx 9\%$ and $\approx 2\%$, respectively. On the other side, the classifiers achieve an error rate of $\approx 2\%$ for detection of incorrect bowing pressure in class set (E). This indicates that identification of inaccurate bowings depends on the type of the inaccuracy. However, even the highest error rate of all 500 runs is below 20% (see Fig. 6) and provides very good assumptions about if and what mistake occurs.

class sets	classes	error rate mean	error rate std
(A)	MCF, DCF, SCF	0.02	0.01
(B)	MCS, DCS, SCS	0.03	0.01
(C)	DCF, DIA>90, DIA<90	0.13	0.02
(D)	MCF, MIA>90, MIA<90	0.09	0.02
(E)	MCF, MIA+, MIA−	0.02	0.01

Table 2: Classification results for different class sets.

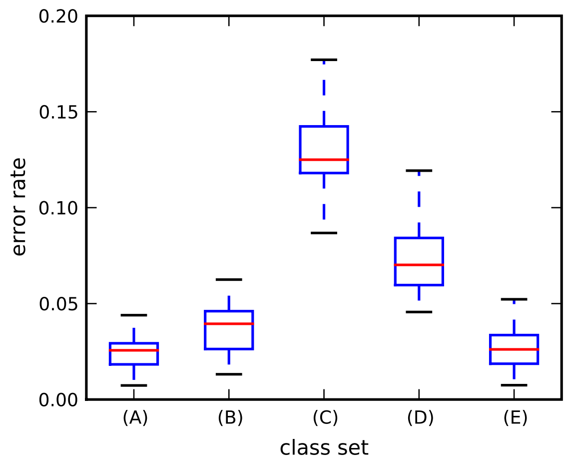

Figure 6: Box plots of the error rates for each class sets from 100 runs. The x-axis denotes the error rate and the y-axis the class set.

5. APPLICATIONS

Pressure sensing has the advantage to measure the "preparation phase" before the bowing or stroke is executed, meaning, the bow does not move, yet. This is a great help in pedagogical areas where it is hard to see pressure. Single finger pressure visualizations can help to explain complex movements and movement preparation phases for simple Detache strokes for beginners or Martele and Spicatto strokes for advanced students. From a technical point of view, the data enable to recognize bowing types even before the movement itself starts.

The data allow the prediction of parameters, such as bow position, type of bow stroke and inaccuracy in the execution. Seeing the pressure and the distribution of the pressure between the fingers allows further examination of how a movement is prepared, executed, and post-processed. Even minuscule balancing moves of the fingers during all of these three phases can be analyzed. Especially during the preparation phase and the post-processing phase where nothing can be hear, every finger can be examined exactly. This "force-loupe" uncovers otherwise hidden pressure patterns and supports the teacher and student in understanding and learning of special bowing techniques like Martele, Spicatto, and Detache, and prevent trembling and cramping.

5.1 Cramping, Jitter, and Nervousness

Cramping is detected by setting certain pressure levels as threshold, whose excess trigger visual or auditory feedback. Even jittering is detected, which which the player can smoothing by activating single fingers. Our experience is that the better the execution of a technical task the smoother the pressure values. This applies to bowing and left hand scenarios, especially at position shifts. Often single fingers start to cramp or tremble, which can lead to uncontrolled vibrato, position shifts, or trembling of the whole bow. Especially when there are slow bowing strokes, "bow trembling" is a well-known problem, which sometimes can be decreased by activating single fingers.

5.2 Extended Scores

Left hand pressure sensing provides additional parameter, which can be used for sound effects, a second voice, or new switching methods for extended scores. For example the position and the pressure of the thumb in the left hand allows on the one hand thumb-steered real-time interaction with electronic peripheries like computers and synthesizers, on the other hand switching, manipulating and mixing of sound effects, accompaniment and 3d-spatial sound position.

5.3 Teaching, Playing, and Exercising

Visualizing the pressure distribution enables a better analysis and understanding of movements, since it allows to see the course in addition to its audible effects. This means e.g. you can hear an inaccurate left hand position change, but not, where the hand coordination goes wrong to cause a bad sound. Pressure changes of the fingers give a hint where to investigate the cause-and-effect chain. Furthermore, the good results of bowing type and accuracy recognition support the students in every-day exercising situations, especially if the accuracy decreases, caused by fatigue.

5.4 Efficient Playing

Many students play with too much force in the left hand, which can be measured and visualized with our system. The correct grasping force allows more efficiency and usually higher playing speed combined with less tiredness. Appropriate feedback can help to reduce physical playing costs by supporting the player to optimize the applied finger forces, which is very important for professional players who have to play for many hours.

6. CONCLUSIONS

The combination of single finger pressure measurements and advanced data mining techniques show a promising way of recognition of different bowing styles, left/right coordination, cramping detection, and many more possibilities as information source for useful tools for every-day exercising and teaching.

The full potential of this measuring method is only tapped so far. Better visualization methods and a stand-alone embedded solution will be the next steps. Since gesture is a very important part in teaching and explaining the complex movements, we have developed our system to allow pressure data visualization, especially in complex preparation and execution phases of a bowing or movement in general.

In combination with position recognition and acceleration sensors, many important parameters can be detected. Our pressure and force sensors also provide many more possibilities for new music compositions in combination with extended scores and simplified real-time interaction within electronic environments. In this ares the main goal will be the integration of the pressure sensors in common musical instrument playing modes and gestures.

7. ACKNOWLEDGMENTS

The work has been supported by CITEC – Center of Excellence in Cognitive Interaction Technology.

8. REFERENCES

[1] F. Bevilacqua, N. Rasamimanana, E. Fléty, S. Lemouton, and F. Baschet. The augmented violin project: research, composition and performance report. In *NIME '06: Proceedings of the 2006 conference on New interfaces for musical expression*, pages 402–406, Paris, France, France, 2006. IRCAM — Centre Pompidou.

[2] C. J. Burges. A tutorial on support vector machines for pattern recognition. *Data Mining and Knowledge Discovery*, 2:121–167, 1998.

[3] C.-C. Chang and C.-J. Lin. *LIBSVM: a library for support vector machines*, 2001. Software available at http://www.csie.ntu.edu.tw/~cjlin/libsvm/.

[4] M. Demoucron, A. Askenfelt, and R. Causse. Measuring bow force in bowed string performance: Theory and implementation of a bow force sensor. *Acta Acustica united with Acustica*, 95:718–732(15), July/August 2009.

[5] C. Flesch. *Das Klangproblem im Geigenspiel.* Berlin : Ries & Erler, 1954.

[6] U. Großekathöfer, T. Lingner, H. Ritter, and P. Meinicke. What is a hidden markov model without transition probabilities? *Neural Computation*, 2010 (submitted).

[7] T. Grosshauser. Low force pressure measurement: Pressure sensor matrices for gesture analysis, stiffness recognition and augmented instruments. In A. C. Stefania Serafin, Gualtiero Volpe, editor, *8th International Conference on New Interfaces for Musical Expression NIME08*, 2008.

[8] H. Kinoshita and S. Obata. Left hand finger force in violin playing: Tempo, loudness, and finger differences. *J. Acoust. Soc. Am. Volume 126, Issue 1*, pages pp. 388–395, 2009.

[9] R. Koehly, D. Curtil, and M. M. Wanderley. Paper fsrs and latex/fabric traction sensors: methods for the development of home-made touch sensors. In *NIME '06: Proceedings of the 2006 conference on New interfaces for musical expression*, pages 230–233, Paris, France, France, 2006. IRCAM — Centre Pompidou.

[10] E. Maestre. *Modeling instrumental gestures: an analysis/synthesis framework for violin bowing.* PhD thesis, Universitat Pompeu Fabra, 2009.

[11] E. Maestre. Statistical modeling of violin bowing parameter contours. Montreal, Canada, 2009.

[12] K. Ng. 3d motion data analysis and visualisation for technology-enhanced learning and heritage preservation. In *AIKED'09: Proceedings of the 8th WSEAS international conference on Artificial intelligence, knowledge engineering and data bases*, pages 384–389, Stevens Point, Wisconsin, USA, 2009. World Scientific and Engineering Academy and Society (WSEAS).

[13] L. R. Rabiner. A tutorial on hidden markov models and selected applications in speech recognition. In *Proceedings of the IEEE*, pages 257–286, 1989.

[14] N. Rasamimanana, D. Bernardin, M. Wanderley, and F. Bevilacqua. String bowing gestures at varying bow stroke frequencies: A case study. In *Lecture Notes in Computer Science*, volume 5085, pages 216–226. Springer Verlag, 2008.

[15] A. J. Smola and B. Schölkopf. A tutorial on support vector regression. Technical report, Statistics and Computing, 1998.

[16] D. Young. Wireless sensor system for measurement of violin bowing parameters. In *Stockholm Music Acoustics Conference (SMAC 03)*, Stockholm.