Posture Identification of Musicians Using Non-Intrusive Low-Cost Resistive Pressure Sensors

Dario Cazzani

Notam
Sandakerveien 24D, Bygg F3
N-0473 Oslo
Norway
dariocazzani@gmail.com

ABSTRACT

The following paper documents the creation of a prototype of shoe-soles designed to detect various postures of standing musicians using non-intrusive pressure sensors. In order to do so, flexible algorithms were designed with the capacity of working even with an imprecise placement of the sensors. This makes it easy and accessible for all potential users. At least 4 sensors are required: 2 for the front and 2 for the back; this prototype uses 6. The sensors are rather inexpensive, widening the economic availability.

For each individual musician, the algorithms are capable of "personalising" postures in order to create consistent evaluations; the results of which may be, but are not limited to: new musical interfaces, educational analysis of technique, or music controllers.

In building a prototype for the algorithms, data was acquired by wiring the sensors to a data-logger. The algorithms and tests were implemented using MATLAB. After designing the algorithms, various tests were run in order to prove their reliability. These determined that indeed the algorithms work to a sufficient degree of certainty, allowing for a reliable classification of a musician's posture or position.

Author Keywords

MATLAB, pressure sensors, posture recognition, standing musicians, educational applications

1. INTRODUCTION

Computer vision and image processing techniques appear to be accurate methods for gesture and posture recognition.

However, pressure sensors under the soles of shoes allow for increased mobility and are more accurate for detecting non-visual corporal behaviours. Research into using pressure sensors for posture detection has been widely conducted by the medical field and for athletic training [1, 2, 8].

This prototype is able to detect the shifting weight of musicians, opening up a variety of opportunities: tutoring systems for educational purposes, individual tutoring for professionals, new musical interfaces, controllers, etc.

Because of this malleability, the algorithms were designed for developing a general-purpose device. It was made to be low in cost and non-invasive for the same reason.

Professional musicians may be aware of the tight relationship between body gestures and performative quality. Some of these gestures are difficult to detect, such as rotational movements above the ankles and head/arm movements. Yet most of these actions have an indirect effect on the musician's weight shifting.

Therefore, the underlying (but still to be proved) assumption is that posture identification through detection of weight shifting can produce information that can be used to evaluate certain aspects of performative quality.

Lastly, by having this prototype in mind as a device for designing new interfaces, weight shifting in the body appears to be an easy and comfortable parameter to control during performances.

Henceforth, the output of the prototype that was built to test the algorithms describes shifting weight comparing a personalised "neutral" weight-position to various other stances of the performer.

2. MATERIALS AND METHODS

2.1. Sensors and soles prototype

The prototype has been sized to fit a variety of foot sizes (European standard 38-44). Therefore, the placement of the resistive sensors is not precise, but they are roughly placed two in the front (just below the toes) and one in the back (more or less where the heel is). The prototype is based on the Funky Soles developed at the University of Oslo [7]. By placing the sensors between two strips of thin wood, see figure 1, their area of sensitivity was enlarged in the most noninvasive manner.

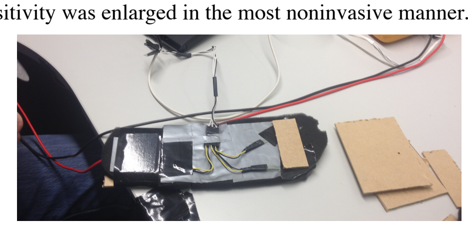

Figure 1: Sensors placement.

2.2. Matlab

The software used for analysis and calculations is MATLAB version R2014a (8.3.0.532). The presence of a broad variety of manuals and informative resources on the Statistics Toolbox™ was considered when choosing this software [5].

2.3. How to acquire data

Data is acquired through a data-logger NDL485 (www.wilmer-s.com), at a sample-rate of 20 Hz and with a resolution of 16 bit. While the Funky Soles [7] have been developed to perform movement classification (such as recognising different gaits, foot tapping or jumping), the core of the algorithm described in this paper is the ability to detect shifting weight comparing a personalised "neutral" weight-position to weight deviations.

Therefore, the first step is to record data classified as the neutral position and use it as a reference. We define the neutral position as when the musician is standing in a comfortable and still position with or without an instrument.

Once the calibration data is acquired the real test can start. Test-data is acquired in two different ways: semi-supervised and unsupervised with video-feedback. In the semi-supervised method, 4 persons were asked to shift in certain directions which were afterwards labeled for testing the algorithm. It is a semi-controlled method because the accuracy with which a person shifts is not reliable; individuals are imprecise.

For the unsupervised method, musicians were asked to perform an instrument and move freely while a camera recorded the actions. To test the algorithms, I would confront what I saw with the output of the algorithms.

3. ALGORITHMS AND OUTPUT

All the following algorithms have been implemented using MATLAB and the codes can be download at http://notam02.no/proj

3.1. From 6 sensors to a 2-dimensional polar representation

The first step is to reduce the dimensionality of the problem from n sensors, 6 in our case, to a 2-dimensional cartesian and then polar representation. It is assumed that the musician is moving on a horizontal surface. A major advantage of a 2-dimensional representation is working with a reduced amount of data. Furthermore, the output presented is clear and user friendly.

A polar representation is the best way to visually represent how the user is moving, where ϱ describes the amount of deviation from the neutral position, and θ describes the direction.

```
// Cartesian values for the n-th sample
// of the neutral position
```

$$Yneutral_n = LB_n + RB_n + (H \cdot M) - (LH_n + RH_n)$$
$$Xneutral_n = RB_n + RH_n + (L \cdot M) - (LH_n + LB_n)$$

```
// Zeros for a 4 quadrant cartesian representation
```

$$Y_0 = \frac{1}{S}\sum_{n=1}^{S} Yneutral_n$$
$$X_0 = \frac{1}{S}\sum_{n=1}^{S} Xneutral_n$$

```
// Cartesian and polar values for an input 'data'
```

$$Y_{data} = (LB_{data} + RB_{data} + (H \cdot M) - (LH_{data} + RH_{data})) - Y_0$$
$$X_{data} = (RB_{data} + RH_{data} + (L \cdot M) - (LH_{data} + LB_{data})) - X_0$$
$$\varrho = \sqrt{X_{data}^2 + y_{data}^2}$$
$$\theta = atan2(Y_{data}, X_{data})$$

Figure 2: Formulas for calculating the 2-dimensional polar representation.

Data from the sensors are divided into 4 groups: data from sensors under the ball of the right foot (RB), sensors under the ball of the left foot (LB), sensors under the heel of the right foot (RH) and sensors under the heel of the left foot (LH).

Given:

- [0, M] = range of output for each sensor.
- M = maximum value the sensors can have.
- H = number of sensors under the 2 heels.
- L = number of sensors under the left foot.
- S = number of position acquired during the calibration.

ϱ and θ are obtained as shown in figure 2.

3.2 From calibration to a function defining the neutral position boundaries

As previously mentioned, because the outcome solely describes shifting weight comparing a personalised "neutral" weight-position to various other stances of the performer, the algorithm determines the set of values which are then classified as "neutral". Anything outside this set will be classified as "shifting" in any direction.

From the calibration process we easily obtain the four representative values of the neutral position, one for each main direction:

$$\varrho_{Right} = \varrho_{Left} = \sigma_x = \frac{1}{\sqrt{S}} \cdot \sqrt{\sum_{n=1}^{S} (Xneutral_n - X_0)^2}$$
$$\varrho_{Forward} = \varrho_{Backward} = \sigma_y = \frac{1}{\sqrt{S}} \cdot \sqrt{\sum_{n=1}^{S} (Yneutral_n - Y_o)^2}$$

Figure 3: Representative values for the neutral position

These last formulas are the standard deviation of the values acquired during the calibration. Unlike the median absolute deviation, this measure of scales is non-robust, meaning that it is influenced by outliers [4]. Robustness is not needed because what we are looking for is an estimation of the width of the set of values which describes the neutral position. Outlier values are therefore important and must be taken into account.

By performing the trigonometric interpolation [3] along the interval θ = [0, 2π) of the 4 values of ϱ calculated as in figure 3, we obtain the function $f_{np}(\theta)$ which represents the borders of the two sets: "neutral position" and "shifting in any direction".

Therefore, given an input data and its polar representation evaluated using the formulas in figure 2, it is then possible to determine wether the input represents the user being in the neutral position or shifting in any direction. The function $f_{np}(\theta)$ is determined by its phase, amplitude and translation (vertical sliding) as shown in Figure 4.

$$amplitude = \frac{1}{2} \cdot |\sigma_x - \sigma_y|$$
$$if(\sigma_x < \sigma_y)$$
$$\quad transl = \sigma_x + amplitude$$
$$\quad f_{np}(\theta) = transl + (amplitude \cdot cos(2\theta + \pi))$$
$$elseif(\sigma_x > \sigma_y)$$
$$\quad transl = \sigma_y + amplitude$$
$$\quad f_{np}(\theta) = transl + (amplitude \cdot cos(2\theta))$$

Figure 4: Amplitude, phase and vertical sliding.

Figure 5 and 6 show an example of a cartesian and a polar representation for the function $f_{np}(\theta)$

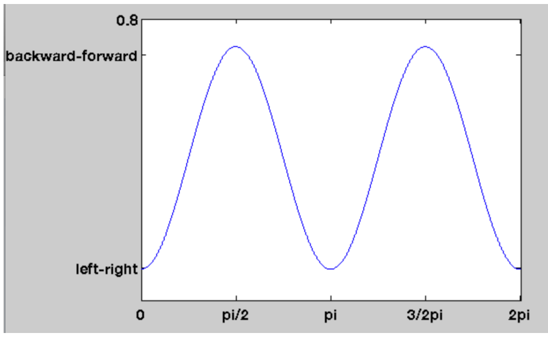

Figure 5: Cartesian representation.

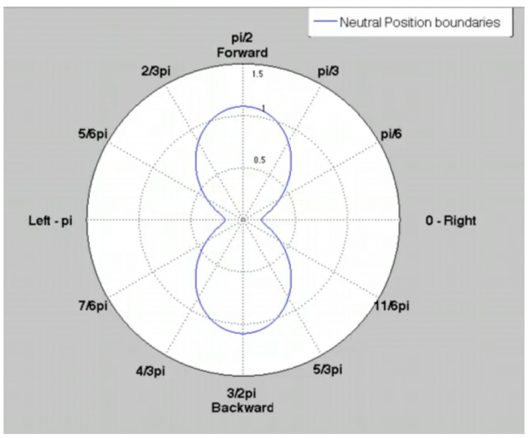

Figure 6: Polar Representation.

3.3. Directions and shifting degree

In order to describe in which direction the user is shifting his or her weight, the interval $[0, 2\pi)$ has been divided into 8 uniform smaller intervals. This division is arbitrary and can be easily customised.

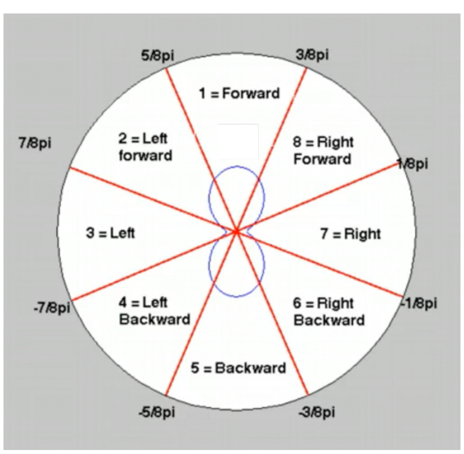

Figure 7: Polar representation subdivided into 8 categories.

Given an acquired data $input = (\varrho_1, \theta_1)$ and its polar coordinates, it is possible to determine the direction by determining in which interval θ_1 belongs to.

The shifting degree is calculated as: $shift = \frac{\varrho_1}{f_{np}(\theta_1)}$

4. RESULTS

4.1. Semi-supervised tests

As mentioned in section 2.3., the musician was asked to shift in certain directions in order to label the positions required to test the accuracy of the output. Because an individual's judgment of shifting his/her own weight is inaccurate, the test results were sometimes slightly inconsistent, even on an individual level. Secondly, the output provided is an estimation of how much the person is shifting, comparing the postures to the neutral position. It is not an absolute description, but it is proportional and automatically calculated relatively to the values found during the calibration process. Taking that into consideration, the tests were evaluated using a Fuzzy Linguistic Description: the numerical output of the algorithm has been transformed in linguistic variables which are less precise but more understandable and closer to human reasoning.

Linguistic variables are variables whose arguments are words, just like in human thinking, and are utilised to give a "value" to an element [6].

The results are, as visible in Table 1, divided into 3 categories: "Correct", "Quite Correct" and "Incorrect". Results are considered correct when the algorithm output matches the labels very well. Results are considered "Quite Correct" when either the direction or the shifting degree is slightly mismatching (for example if a posture is labelled as "Forward" and the output is "Left Forward). The results are considered "Incorrect" otherwise.

Table 1. Results of the semi-supervised tests

	Correct	*Quite Correct*	*Incorrect*
User 1	95%	3%	2%
User 2	93%	3%	6%
User 3	96%	2%	2%
User 4	75%	16%	9%

The numbers shown above demonstrate a high percentage of accuracy for the first three users. Inversely, the Incorrect percentages are quite low which shows the relative reliability of this device. It is assumed that the incorrect tests are primarily attributed to minor imperfections of the prototype and occasionally making some of the sensors incapable of perceiving weight. The levels of accuracy for user 4 were lower due to a small foot size and therefore it is assumed that for several of the tests, they failed to apply enough pressure on the sensors.

Figure 8 is an example of 4 tests recorded from user 1. Each segment is 40 seconds long. The expected values are depicted in the legend at the bottom of the right-hand side.The left side depicts the system's recognition of the inputs. The lines represent the directions perceived by the system. As mentioned above, the space has been arbitrarily divided into 8 directions, but it can be quantised as precisely as needed. The shifting degree is not represented.

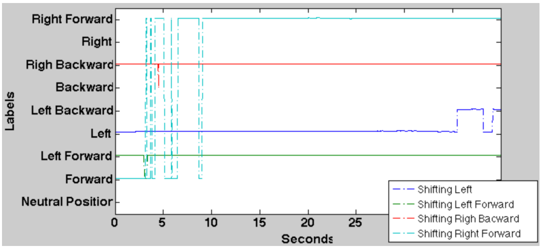

Figure 8: Time series of the directions identified by the system.

4.2. Tests with video-feedbacks

For the second testing method, a musician uses the system while performing a piece which is recorded in a video and then compared to the output of the system. Figure 9 shows a frame from one of the videos taken during the tests and a graphical output of the system at the same instant. This test was run while detecting the postures of a violinist, yet the soles are designed for any standing musician.

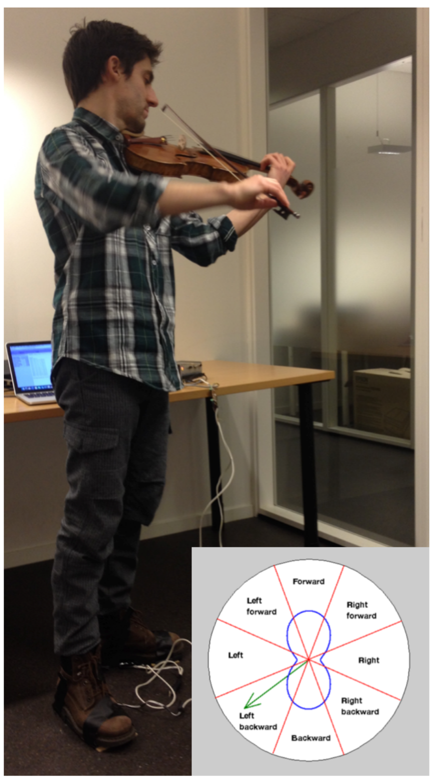

Figure 9. A Violinist performing using the soles prototype and a graphical representation of his posture.

The viewer's interpretation of the video was only able to give an approximation of the body weight shifting therefore the comparison itself is approximate. However, even on a visual level, the prototype appeared to be accurate.

5. DISCUSSION

5.1. Future work

As described above this prototype can be the base for building an interface for diverse purposes and devices.

As an interface it can be integrated into various systems and can function as a music controller.

Another interesting aspect would be its possible uses as part of an educational tool. Providing hidden information concerning the musician's movements, it allows teachers to analyse their students techniques and habits which are undetectable through a visual approach. Additionally, by developing appropriate pattern recognition algorithms, it is in theory possible to develop a tutoring system which would confront, from a corporal behaviour point of view, different performances of the same musical pieces and provide significant data for improving musicians' performances.

5.2 Improvements in the prototype and testing methods

The prototype presented in this paper lacks portability and flexibility. The next step is to build a wireless interface which would allow the musician to move freely. Even if the prototype has been designed to fit a variety of foot sizes, results for user 4 show that the possibility to replace the sensors for individual user would increase the efficiency of the device. Moreover, it is not completely comfortable. A possible solution would be to sew the 6 sensors to a pair of socks or use e-textile pressure sensors for a better user experience. This prototype was designed for detecting the weight shifting of standing musicians, yet the same algorithms applied to sensor located on the chairs of seated musicians (such as pianists) are believed to produce similar results. Another prototype would be needed in order to verify these claims. More accurate and precise tests may be designed in other manners, all with the goal of a proper supervised method for results analysis.

6. ACKNOWLEDGEMENTS

I would like to express my gratitude to Hans Wilmers for his help in building the prototype and reviewing this paper. I would like to thank the University of Oslo for providing me the Funky Soles and letting me adapt them for the experiments. Thanks also to Notto J. W. Thelle, head of NOTAM, for his time and for allowing me to use NOTAM's resources. Special thanks to Taylor A. S. Sánchez for her precious help in reviewing this paper.

7. REFERENCES

[1] J. J. Liu, W. Xu1, M. Huang, M. Sarrafzadeh, N. Raut, B. Yadegar "A Dense Pressure Sensitive Bedsheet Design for Unobtrusive Sleep Posture Monitoring"

[2] J. Pauk, J. V. Raso, K. Daunoraviviene, M. Ihnatouski "Analysis of the plantar pressure distribution in children with foot deformities" in *Acta of Bioengineering and Biomechanics Vol. 12, No. 1, 2010.*

[3] A. Quarteroni, F. Saleri "Scientific computing with Matlab" in *Chapter 3 of Approximations of functions and data.*

[4] P. J. Rousseeuw and C. Croux "Alternatives to the Medi an Absolute Deviation" in *Journal of the American Statistical Association Vol. 88, No. 424 (Dec., 1993),*

[5] Statistics Toolbox™ User's guide: http://www.mathworks.com/help/releases/R2014b/pdf_doc/stats/stats.pdf

[6] P. Ponce-Cruz, F. D Ramírez-Figueroa, "Intelligent Control Systems with LabVIEW" in *Chapter 2 "Fuzzy logic".*

[7] K. Nymoen, S. Song, Y. Hafing, J. Torresen "Funky Sole Music: Gait Recognition and Adaptive Mapping".

[8] Thomas Holleczek, Alex Rüegg, Holger Harms, Gerhard Tröster "Textile Pressure Sensors for Sports Applications".