

Rocking out in a chair?

Physiological signal processing to detect dancing activity in a seated listener

Listening with motion

Motion is a common and prominent component of many listeners' responses to many kinds of music.

Even when seated, listeners can engage in restrained dance-like motor activity like head-nodding, torso swaying and foot tapping. For some, this physical accompaniment is felt to be essential to normal engagement with music.

Objective: Detection of listener behaviour

Using a common suite of physiological sensors monitoring a listener's response to musical stimuli:

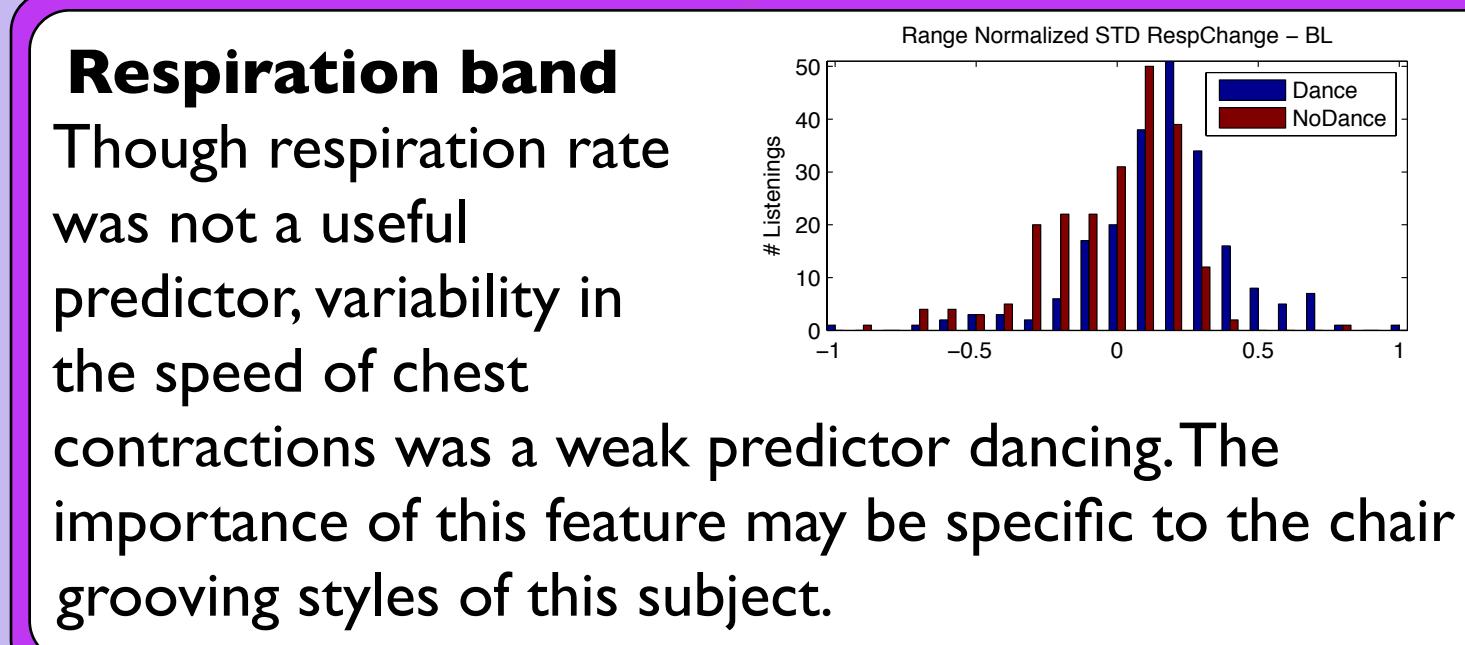
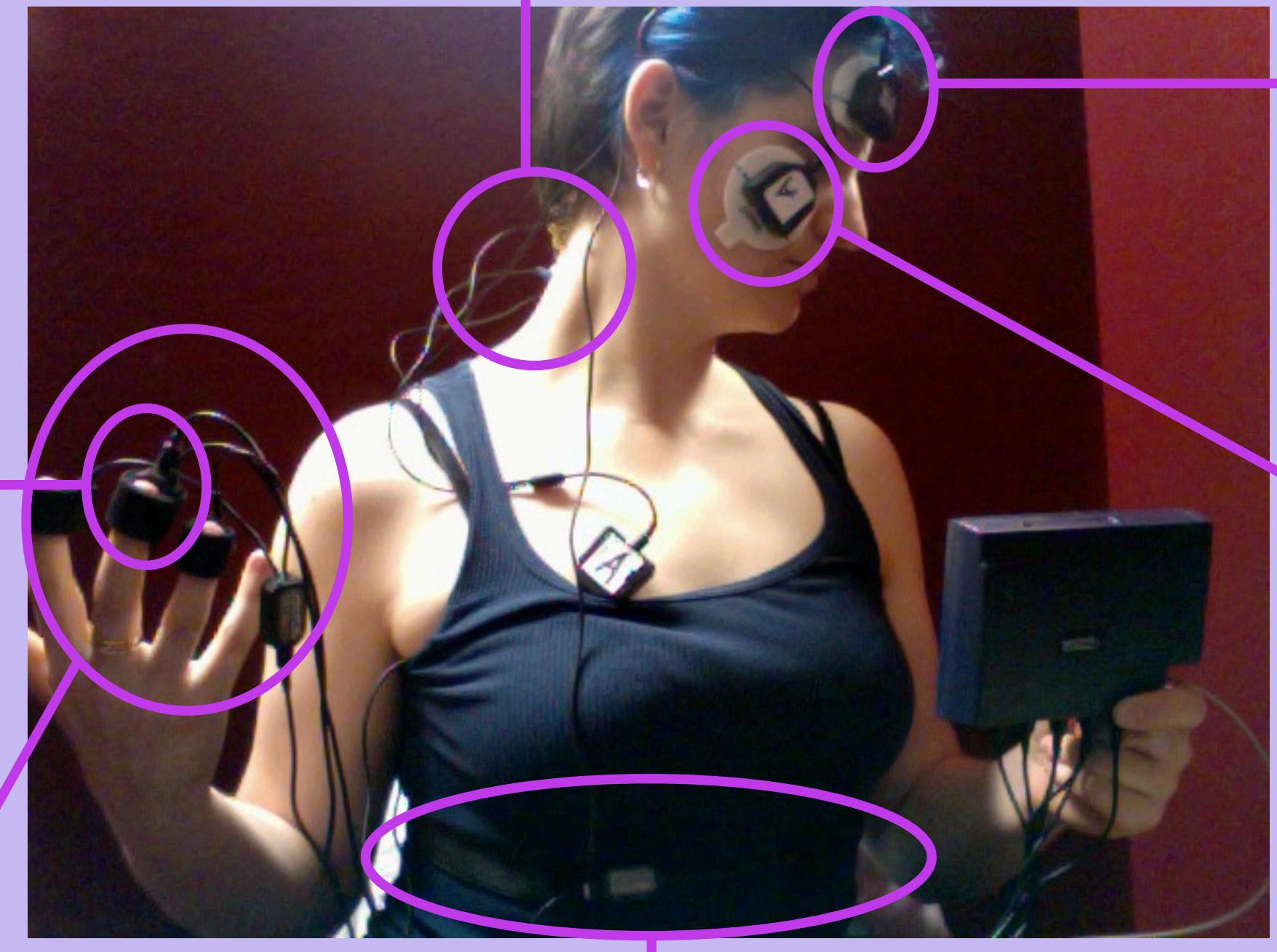
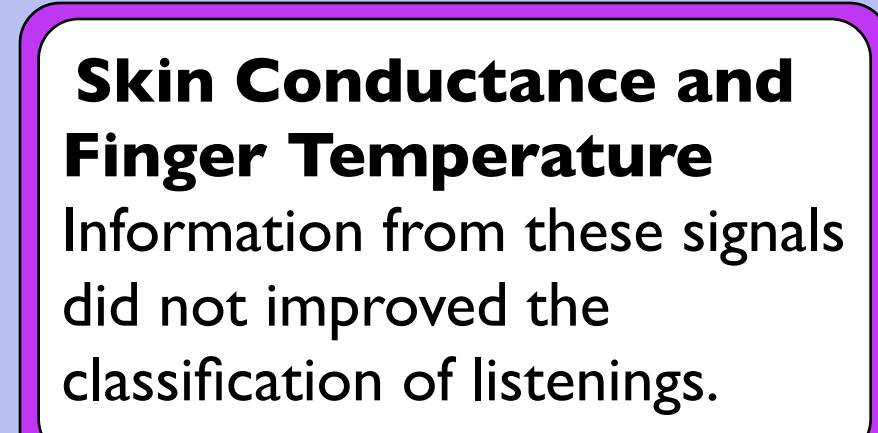
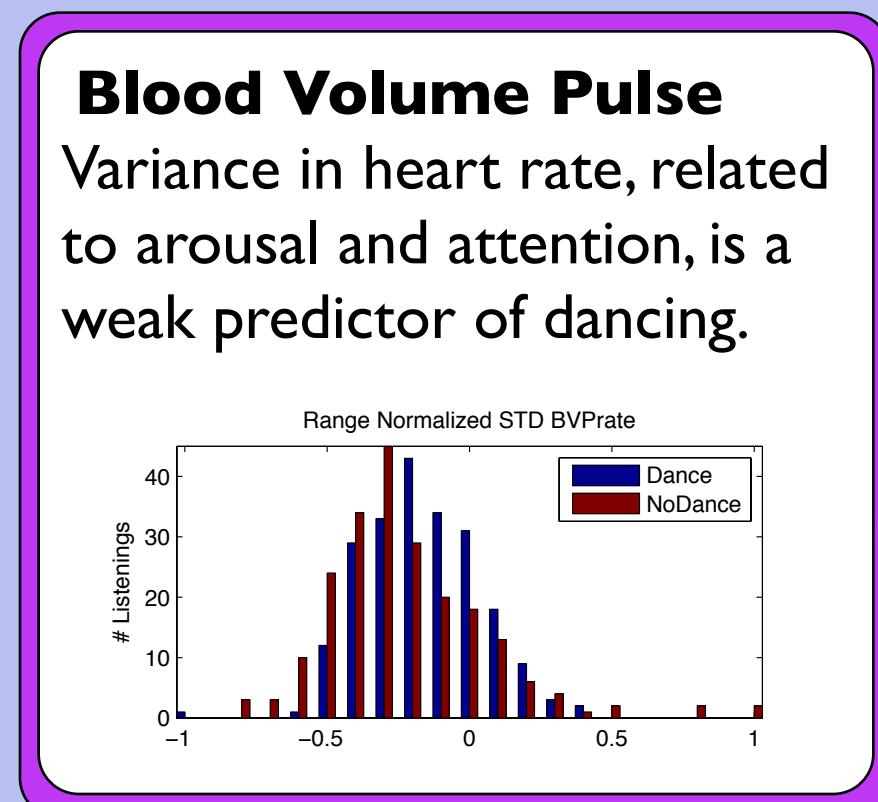
1. Which signals are affected by dance-like activity?
2. Can sensor data identify dance behaviour during listening?

Data set: Solo Response Project

Continuous physiological responses and felt emotion ratings from one subject, collected during repeated listenings to a randomly ordered set of musical stimuli.

Of 600 listenings, subsets were selected and annotated for dancy-ness.

Classification of dancing and not dancing per listening and listening excerpt used post-experiment subjective grooviness ratings of the stimuli, plus notes on the subject's engagement collected during experiment.



Bar graphs display the distributions of range-normalized feature values for both classes of listenings. 216 listenings to high groove stimuli, 216 listenings to low groove stimuli, each signal time series summarized by a point.

The above photo is of the subject/author of this research.

Results

Using SVM to classify listenings with different combinations of features, a hierarchy of relevant features arose.

Features from the corrugator and trapezius yielded 91% classification.

Features from the zygomaticus, respiration, and heart rate only correctly classified 72% of the listenings.

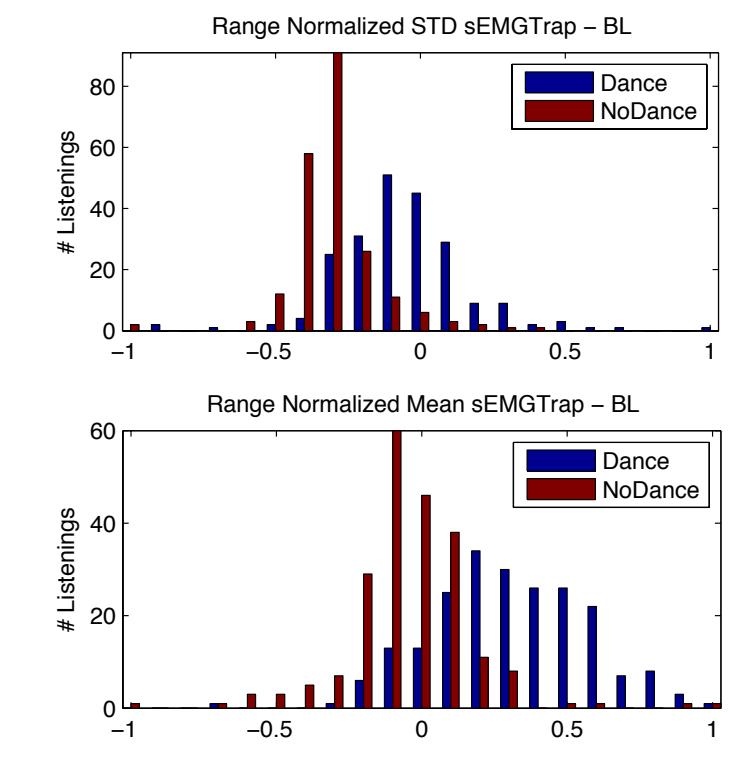
Notes on Errors

Why not 100%? Compromised ground truth. The tags reflect the stimulus alone, but the participant did not always respond to the groovy tracks.

From the strong feature classification, a quarter of these errors agree with notes of disengagement and sleepiness. Another third are in proximity of tracks with noted disengagement.

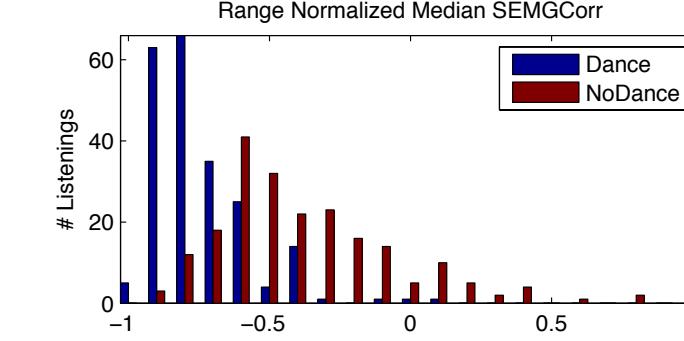
sEMG of the Trapezius

Strong, regular contractions of the upper trapezius (at back of neck) indicate head nodding, while sustained high values accompany strong negative emotions. Variance of sEMG Trap, less baseline, is one of the strongest dance predictors. The average sEMG Trap is also good.



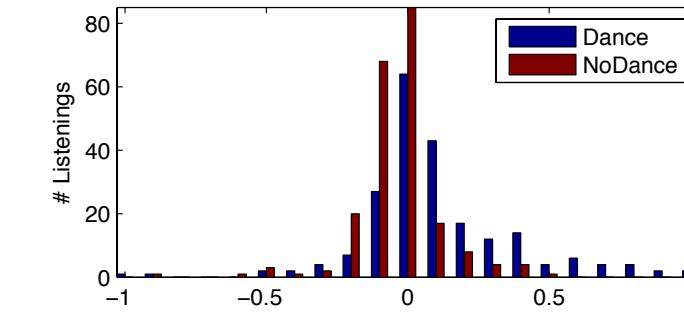
sEMG of the Corrugator

A strong predictor of dancing. Most listenings with low median corrugator activation (brow furrowing) were to groovy tracks. The distinction is remarkable considering the distribution of valence ratings, to which this signal is presumed to be related.



sEMG of the Zygomaticus

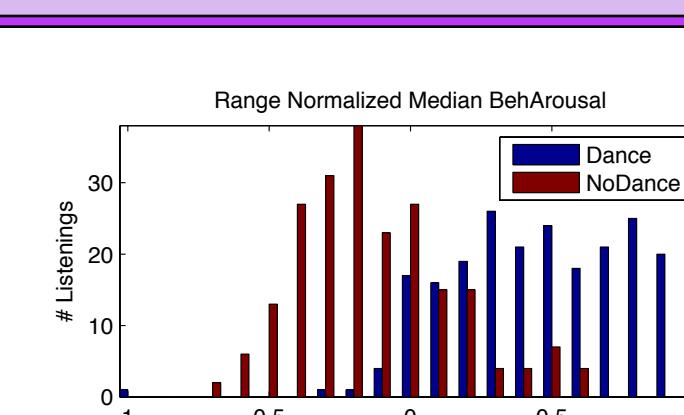
A weaker predictor, but dancing listenings had the highest values (strongest smiles?), despite similar ranges of felt emotional valence.



Felt Emotion Ratings

Median of Felt Emotional Arousal was one of the best predictors, but it is excluded from these analyses because of the subjective source.

Felt Emotional Valence is not an effective predictor of dancing. The distributions of Valence values for dance and nodance are not identical, but they each spread widely over the same range, making discrimination impractical by this feature alone.



Second Evaluation: per 45s interval

Dancing behaviour can change over the course of a piece. This second round uses these same features to evaluate signals over subsections of the music.

Set to train and classify

Dancing and no dancing training set was constructed with listener notes. Dancing tracks were selected of high groove tracks from sessions with pro-dancing notes. Non-dancing tracks were selected from low groove tracks and listenings with notes counter to dancing (i.e. sleepiness). Intervals of dancing tracks were annotated for local grooviness. Total of 33 tracks, 166 intervals tagged Dancing, 206 not.

Results

The strong features classified these segments 83% correctly. Addition of the weaker features raised this score to 86% accuracy.

Notes on Errors

The errors for these classifications were more problematic, and did not always agree with the results of the first evaluation.

Conclusions

Classification of dancy-ness was very successful, both for whole listenings and 45 second excerpts. However, better curated data and listenings from other subjects are needed to determine the relevance of these features to the music inspired motions of the broader public.

Acknowledgments

My thanks to Stephen McAdams and CIRMMT for loaning space and equipment for this experiment at McGill University, to NSERC for supporting my doctoral research, and to my peers and supervisor, Mary Farboud, at NYU.

Bibliography

Etzel, J. A., Johnsen, E. L., Dickerson, J., Tranell, D., and Adolphs, R. (2006). Cardiovascular and respiratory responses during musical mood induction. *International Journal of Psychophysiology*, 61(1):57–69.

Gomez, P. and Danuser, B. (2004). Affective and physiological responses to environmental noises and music. *International journal of psychophysiology: official journal of the International Organization of Psychophysiology*, 53(2):91–103.

Hodge, D. A. (2010). *Handbook of music and emotion: theory, research, applications*, chapter 11, Psychophysiological measures. Series in Affective Science. Oxford University Press.