Support Vector Machine Prediction of Blended Emotional Reactions to Film: Continuous Self-Report, Face and Neck EMG

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Background

Machine learning techniques, such as support vector machines (SVM), are specialized for the integration and utilization of complex patterns in multivariate data. Blended emotional reactions (experience more than one emotion, Larson & McGraw, 2014) are elusive partially due to the dynamic interactions between emotions over time. Errors in powerful SVM predictive models can provide insight into the potential utility of blended metrics ("Min").

Participants

43 (23 female) psychology students

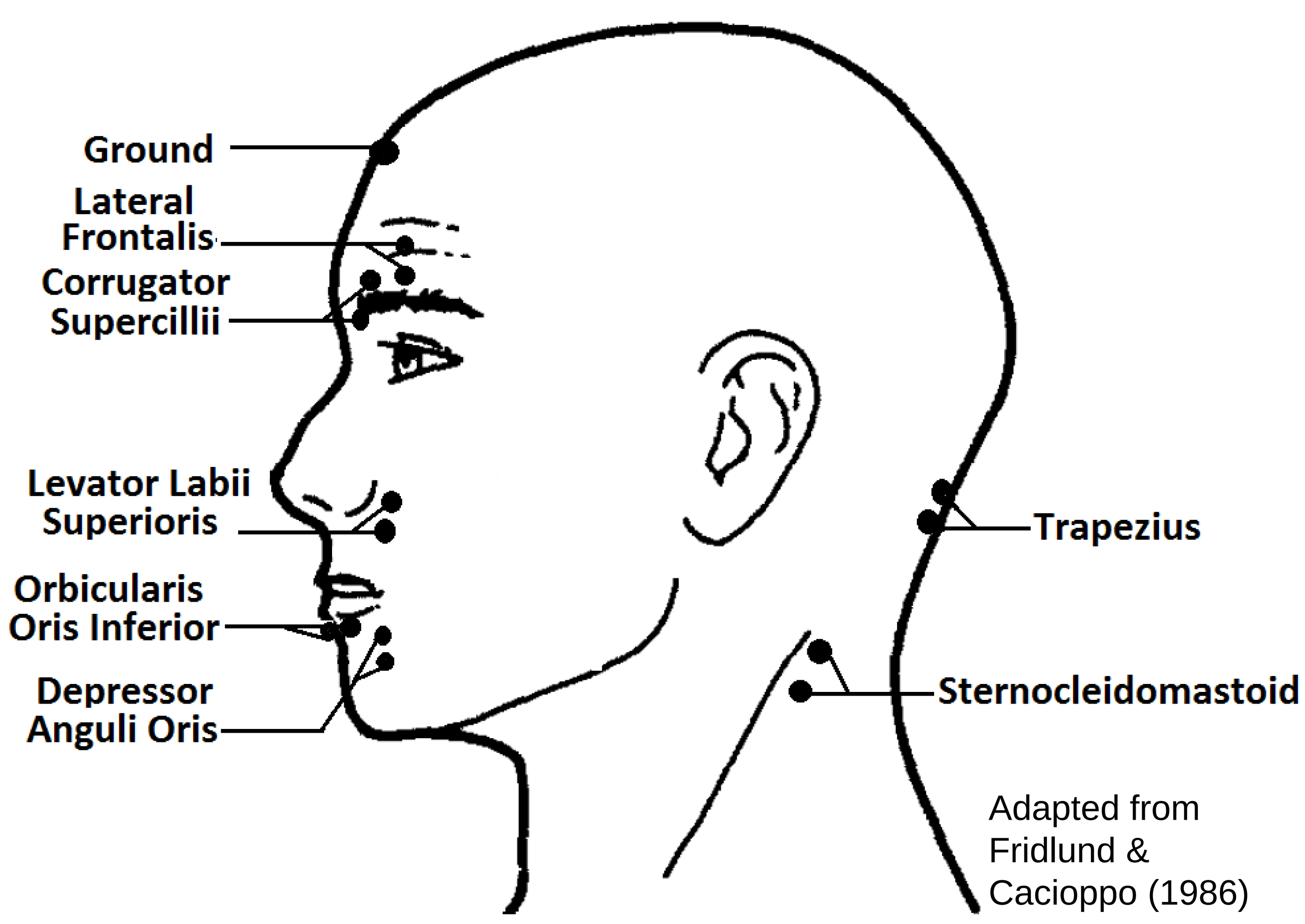
Stimuli

Data collected during blended film clip viewing from the DZA film collection. Duration 1.5-2 min

- 3 elicit anger and moral disgust (Mdisgust)
- 3 fear and pathogenic disgust (Grossed out) (Hutcherson & Gross, 2013).

Electromyography

Bipolar Ag/AgCl electrodes, filtered, rectified, and smoothed (100 ms moving average)



Adapted from Fridlund & Cacioppo (1986)

Continuous Self-Report

- Emotions rated separately during film, but after EMG recording (3 views per film)
- Mouse used for 0-8 scale of intensity
- Lowest of two emotions (Min) used to assess blend between two emotions, calculated for each sample (Kreibig, Samson & Gross, 2013).

Support Vector Machines

- All data averaged to 200 ms bins
- Transformed percent change from baseline
- Trained with data from 60% of participants with *kernlab* (R), Gaussian kernels, using 1 second EMG data per film to predict 1 emotion (the other emotion removed).
- Each observation includes the 2 most recent time bins.
- SVM predictions of emotion were generated from EMG of remaining participants

Analyses

- Multilevel models (MLM), using *nlme* (in R) used to test all hypotheses
- To test the first hypothesis (H1), raw predictions and self-report were used.
- For the last hypotheses (H2 and H3) the root mean squared error (RMSE) for each second was used as a dependent variable

Results

H1) SVM are capable of predicting self report from EMG. Relationship between SVM and self report were assessed with correlations (Table 1) and MLM model variance explained (Table 2). For example of raw see Figure 1.
Fixed only: SVM x *Random*: (Film Type x Emotion + Time) within participant

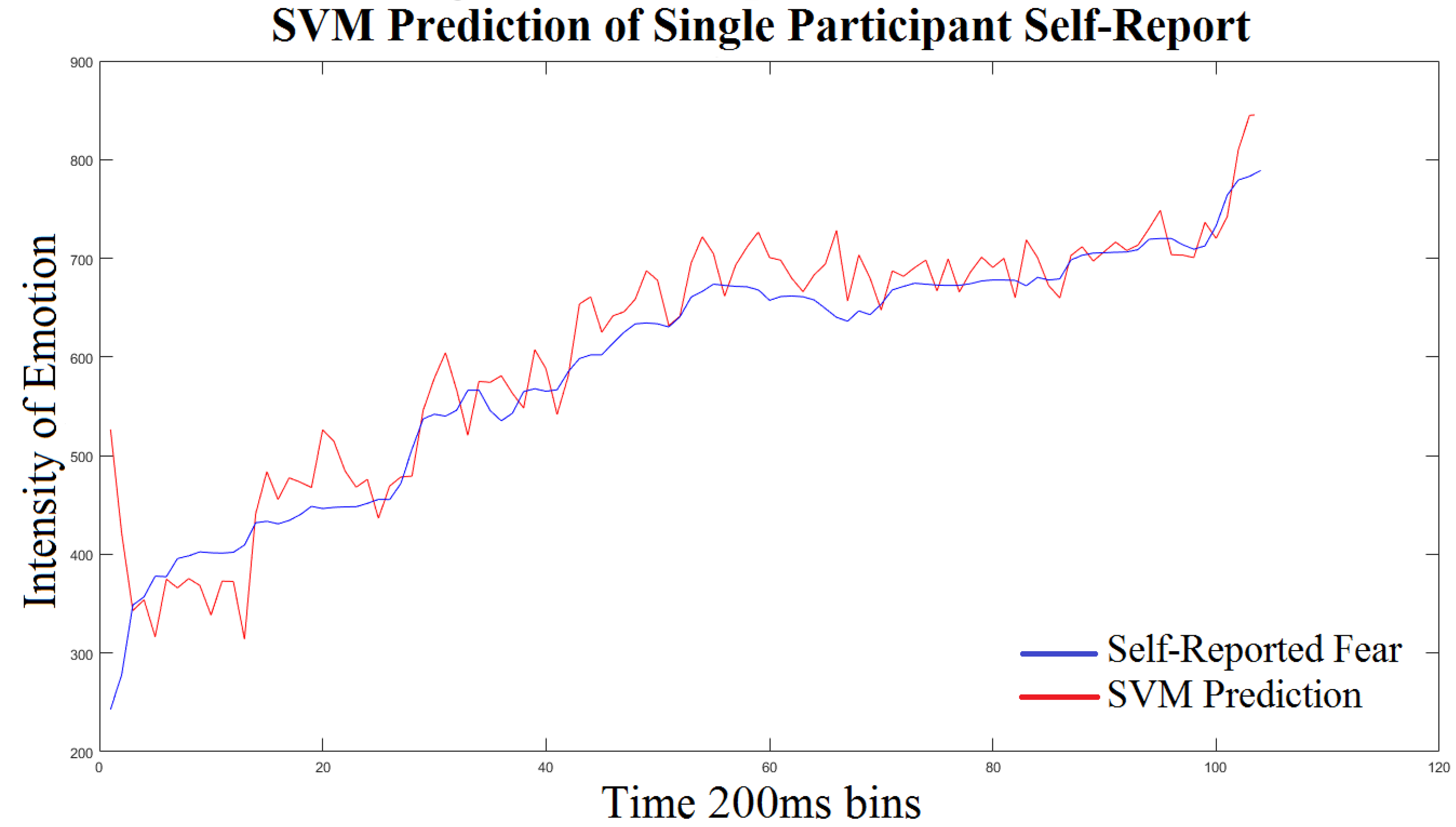
Table 1: Spearman's Rho Correlations Between Self-Report and SVM Predictions

	SVM		SVM
Fear	0.373	Anger	0.421
Gross	0.260	M.Disgust	0.338
Min FD	0.295	Min AD	0.414

Table 2: MLM Fixed Effect and Model Variance Explained for RMSE Predicted by SVM

Fixed Effect Interaction			*Model*	
DF	F-value	p-value	Adj R^2	StdErr
77532	38.886	<.0001	**0.644**	1.592

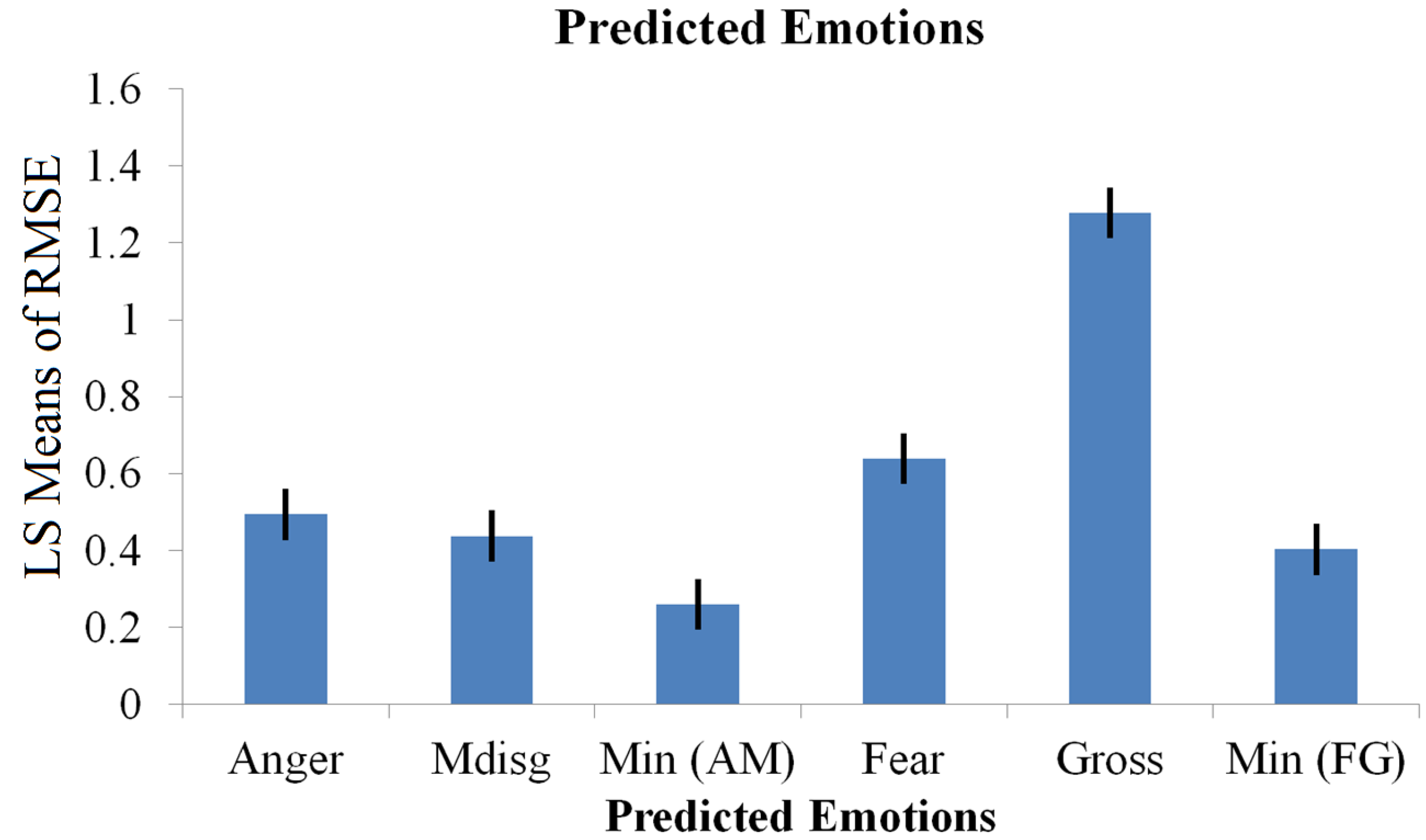
Figure 1: Example Time Series
SVM Prediction of Single Participant Self-Report



H2) Blended emotional reactions will be more accurately predicted than individual emotions for blended films. *Fixed*: Film Type x Emotion

- Least-squared means (lsmeans R) (Figure 2)
- Tukey's pairwise: all emotions differ except moral disgust from anger or Min of fear and grossed out (FG). Anger and moral disgust more accurately predicted by SVM than fear and grossed out. Blended (Min) more accurately predicted than constituent emotions

Figure 2: Least-Squares Means for SVM Predicted Emotions



H3) To assess whether specific channels were essential to SVM predictions, models were also run without 1 or 2 electrodes. No models differed from the full version

Conclusion

- SVM may be useful in prediction of psychological states from EMG. Error can provide insight
- Blends between emotions should be assessed
- Emotions can be predicted from multiple muscles
- In future focus on relative intensity between emotions and types of blending

References

Fridlund, A. J. & Cacioppo, J. T. (1986). Guidelines for human electromyographic research. *Psychophysiology*, 23, 567-589.

Hutcherson, C. A. & Gross, J. J. (2011). The moral emotions: A social-functionalist account of anger, disgust and contempt. Journal of personality and social psychology, 100, 719-737.

Kreibig, S. D., Samson, A. C. & Gross, J. J. (2013). The psychophysiology of mixed emotional states. *Psychophysiology*, 50, 799-811.

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