Automatic Feature Extraction for Social Touch Classification

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Motivation

Tactile Modality is vital in subtle communication and conveying emotion
→ A need for automatic social gesture recognition

Previous Studies
Classification with the Corpus of Social Touch (CoST)

- Manual feature engineering
- Highest accuracy: 60%
  → need better feature extraction to minimize possible humans' errors in hand-picked features

Goal
Automatic and inexpensive feature extraction for accurate classification

Dataset

The Corpus of Social Touch (CoST) - Jung et al. (2017)

- ❑ 14 gestures were captured.
  (Grab, hit, massage, pat, pinch, poke, press, rub, scratch, slap, squeeze, stroke, tap, tickle)
- ❑ 3 variants (gentle, normal, rough)
- ❑ The number of frames: 10 – 1747 (average: 191.78)
- ❑ Each frame consists of 64 channels (8 x 8 sensor grid)
- ❑ The channel values: 0 – 1023

Preprocessing

- ❑ Zero-padded to 1747 x 64
- ❑ Incremented by 1 before zero-padding
- ❑ Training : Validation: Test = 7 : 1 : 2

Experiment

Feature Extraction

ConvLSTM Autoencoder

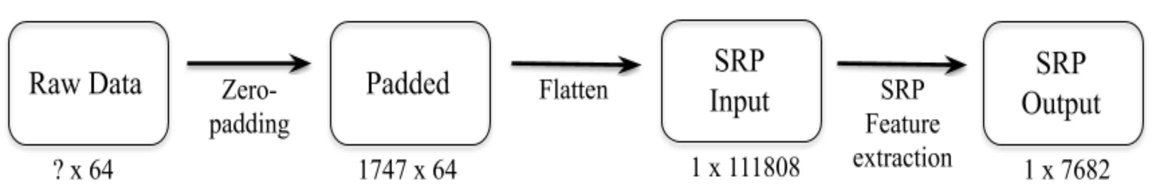
- ❑ Capture spatio-temporal correlation
- ❑ 93,640 trainable parameters
- ❑ Latent representation of size 2048

Principal Component Analysis (PCA)

- ❑ Extract the dominant patterns in the data matrix
- ❑ Output of size 6400

Sparse Random Projection (SRP)

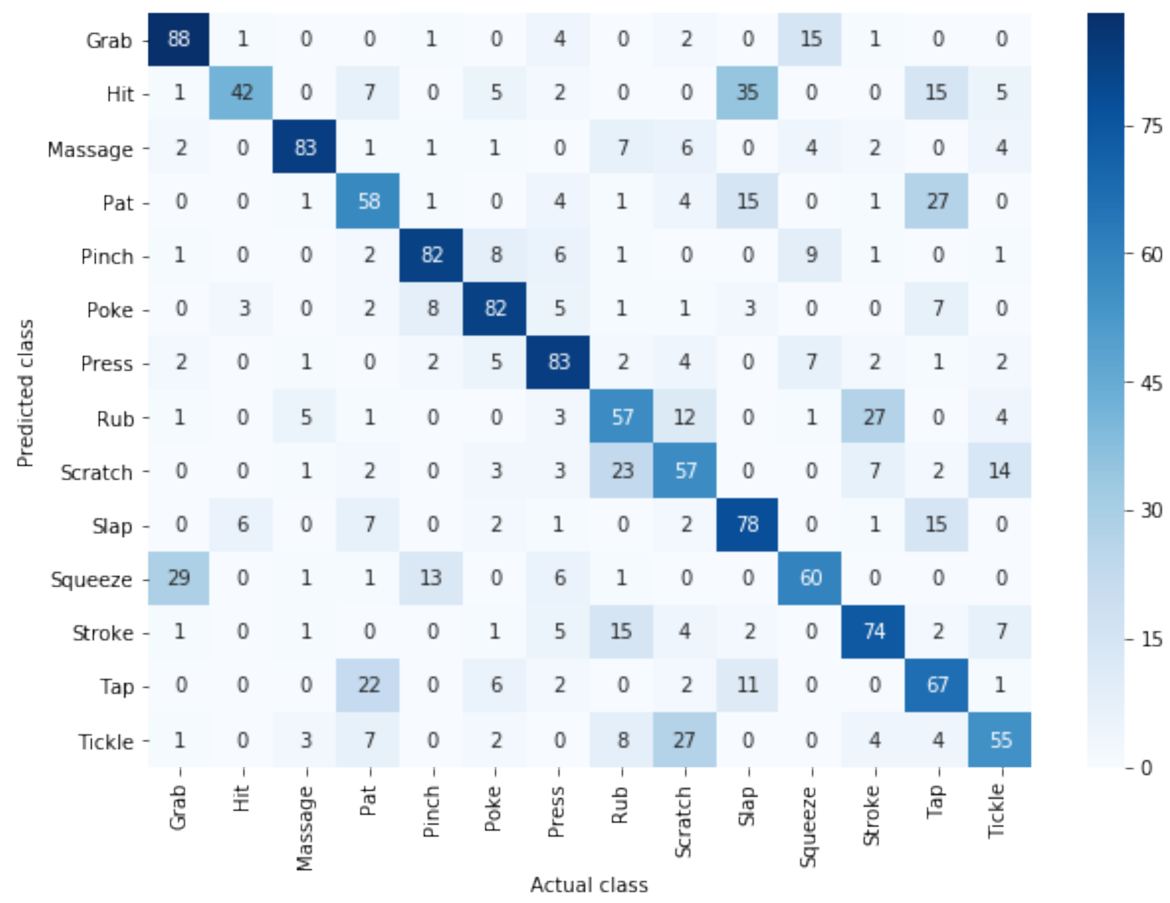
- ❑ Any high dimensional data can be converted into a lower dimensional space through random projection (Johnson-Lindenstrauss)
- ❑ Random projection matrix density: 1/sqrt(n_features)
- ❑ Output size: $n\ components \geq \frac{4\log(n\ samples)}{\varepsilon^2 - \varepsilon^3}$



Results

	ConvLSTM-AE	PCA	SRP
Output size	2048	6400	7682
Training hours	20	4	2
Training accuracy (%)	-	98.45	92.50
Test accuracy (%)	-	29.08	61.88

	All	Gentle	Normal	Rough
SRP-CNN	**.62**	**.58**	**.68**	.60
Bayesian	.57	.52	.59	.58
Decision tree	.48	.43	.49	.52
SVM linear	.59	.54	.60	**.62**
SVM RBF	.60	.54	.60	**.62**
Neural Network	.59	.52	.58	.59

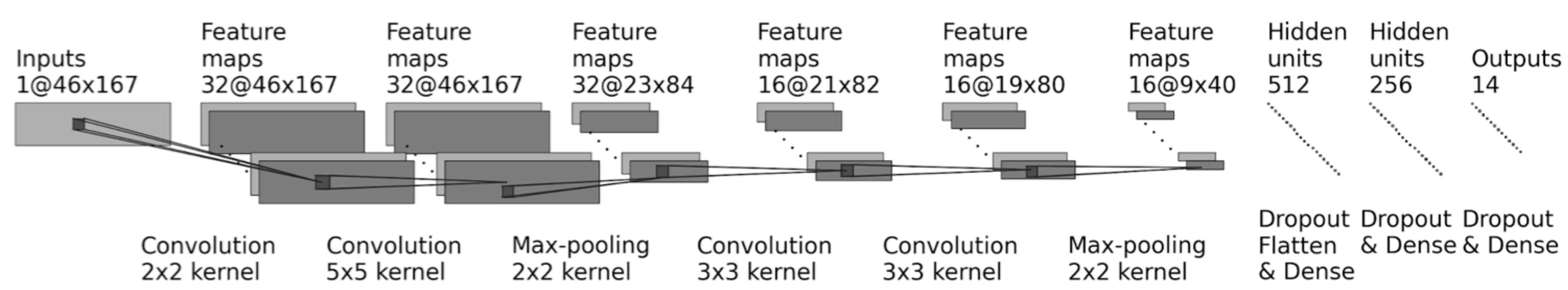


- ❑ SRP showed the best performance with test accuracy 61.88% (M=62%, SD=13%)
- ❑ Misclassification mostly due to similarity in nature between certain gestures
- ❑ Accuracy higher than the models from the previous studies
- ❑ Robust to different gesture variations

Classification

Convolutional Neural Network (CNN)

- ❑ Classified 14 different gestures (not considering variants)
- ❑ Trained 250 epochs for the best performance
- ❑ Loss function: $L(y, \hat{y}) = -\sum_{j=0}^{M}\sum_{i=0}^{N}(y_{ij} * \log(\hat{y}_{ij}))$
- ❑ Optimizer: AdaDelta



Discussion

Future Work

- ❑ Using SRP with different configurations and classifiers for a more optimal projected space
- ❑ Measuring the generalization performance of each pipeline
- ❑ Incorporating data from other modalities or other datasets of the tactile modality may enhance the classification of the gestures

Conclusion

- ❑ A more memory and computation efficient pipeline to classify social touch gestures
- ❑ A stepping stone in developing real-time touch recognition

References

[5] M. M. Jung, Mannes Poel, R. W. Poppe, and D. K. J. Heylen, "Automatic recognition of touch gestures in the corpus of social touch," *Journal on multimodal user interfaces*, vol. 11, pp. 81–96, 2017.

[8] X. SHI, Z. Chen, H. Wang, D.-Y. Yeung, W. Wong, and W. WOO, "Convolutional LSTM network: A machine learning approach for precipitation nowcasting," C. Cortes, N. D. Lawrence, D. D. Lee, M. Sugiyama, and R. Garnett, Eds. Curran Associates, Inc., pp. 802–810, 2015.

[9] Viorica Patraucean, Ankur Handa, and R. Cipolla, "Spatio-temporal video autoencoder with differentiable memory," 2015.

[10] Svante Wold,K. Esbensen, and P. Geladi, "Principal component analysis," *Chemometrics and Intelligent Laboratory Systems*, vol. 2, pp. 37–52, 1987.

[11] Dimitris Achlioptas, "Database-friendly random projections: Johnson-Lindenstrauss with binary coins," *Journal of Computer and System Sciences*, vol. 66, pp. 671–687, 2003.

[13] P. Li, T. J. Hastie, and K. W. Church, "Very sparse random projections," pp. 287–296, 2006.

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