Communicative vs Transitional Features in American Sign Language

Tania Nguyen, Sevgi Gurbuz, Evie Malaia

Department of Communicative Disorders, College of Arts & Sciences

College of Engineering

Background

- **Short term goals**: Create a system for interaction with smart environments (similar to "Hey Google") for Sign Language users
- **Long Terms goals**: Identify dynamic components of ASL signal that are critical to information transfer
- Prior research *(Malaia et al., 2012; 2016; Borneman et al., 2018)* indicated that variability of motion in ASL signal is critical for information transfer.

Methods

- Motion Capture Data (MoCap): full-fidelity 3D recording of raw physical signal from multiple articulators
- ELAN software: video of multiple ASL paragraphs annotated by proficient signers
  - Extract data for Gloss Timestamps
- Why Machine Learning?
  - Applicability to simple classification problems *(Gurbuz et al., 2020)*

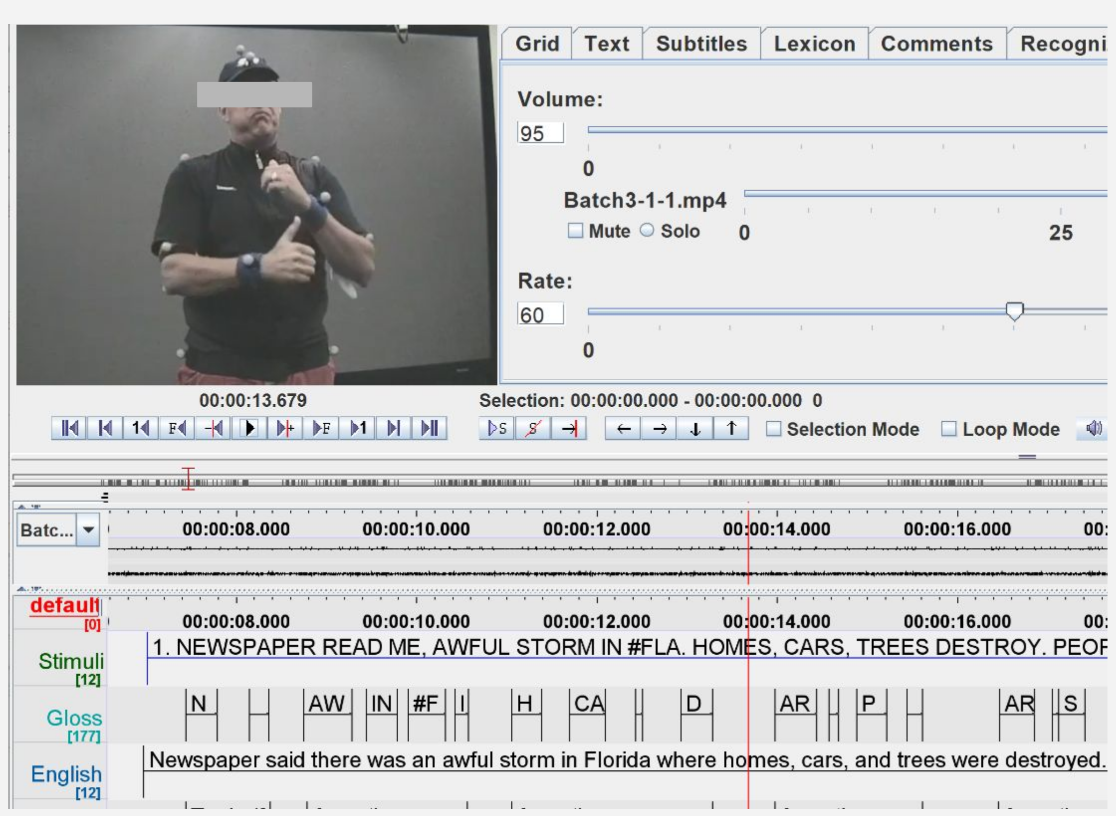

Figure 1: Annotated video in ELAN Software

Sign Lagngauge Uesrs Can Comumniacte simlirarly to how you can raed tihs snetnece.

How can signs be parsed** out from continuous time series data in order to **create a computerized environment?

Results

Alignment of Annotations & MoCap data with Video

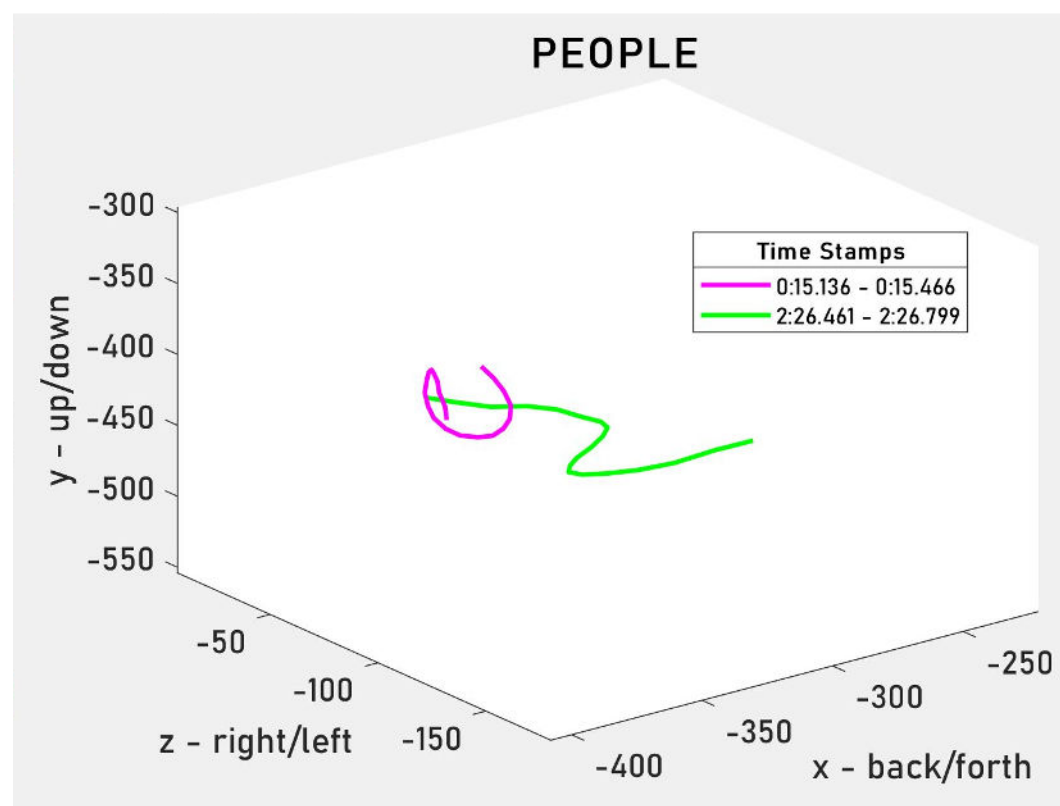

Figure 2: 3D models of same sign at beginning and ending of video

- MoCap: 60 frames per second
- Increasing Offset with Proceeding Time
- Identify Coordinates for each sign & transition time frame

Implement Data sets into Machine Learning

- Transform Raw Data of signs & transitions to velocity vectors

Maximum Accuracy of Machine Learning Methods				
	Random Forest	K-Nearest Neighbor	LDA	SVM
Max & Min Velocities	50.7785%	60.2941%	66.1765%	60.2941%
FFT of velocities	53.3304%	61.7647%	67.6471%	66.1765%

Figure 3: 4 common methods of Machine Learning. Random 80% of data was used to train while 20% was used to test. Percentages represented accuracy of test data

Discussion

- Spectrotemporal information from dominant hand motion during signing is informative to signers (comprehensible w/o handshapes, non-manual markers, etc.)
- ML acts as a method of testing multiple hypotheses simultaneously by narrowing down salient portions of the signal (cf. explainable AI)
- **Capturing entropy fluctuations might require alternative approaches** i.e. :
  - FFT data (real, imaginary, amplitude) with more input data
  - Higher-order displacement derivatives (acceleration, jerk, snap)

Want more details? Scan this QR Code!

Contact

Tania Nguyen

t.h.nguyen@tcu.edu

References

Gurbuz, S. Z., Gurbuz, A. C., Malaia, E. A., Griffin, D. J., Crawford, C., Rahman, M. M., ... & Ozcelik, E. (2020, April). A linguistic perspective on radar micro-doppler analysis of american sign language. In *2020 IEEE International Radar Conference (RADAR)* (pp. 232-237). IEEE.

Borneman, J. D., Malaia, E., & Wilbur, R. B. (2018). Motion characterization using optical flow and fractal complexity. *Journal of Electronic Imaging*, *27*(5), 051229.

Malaia, E., Borneman, J. D., & Wilbur, R. B. (2016). Assessment of information content in visual signal: analysis of optical flow fractal complexity. *Visual Cognition*, *24*(3), 246-251.

Malaia, E., & Wilbur, R. B. (2012). Kinematic signatures of telic and atelic events in ASL predicates. *Language and speech*, *55*(3), 407-421.