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Translating sEMG Signals to Continuous Hand Poses Using Recurrent Neural Networks

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Abstract

- We analyze sEMG signals from the forearm using low cost data acquisition device (Myo)
- We show that hand posture can be successfully estimated from sEMG (about 3.5 mm accuracy)

sEMG for Hand Pose Estimation

- Non-invasive surface electromyogram (sEMG) from the forearm contains useful information for decoding hand kinematics [1, 2]
- sEMG has been used to develop intuitive robotic prosthesis interfaces either via pattern recognition [3]
- Hand pose estimation solutions have been proposed using stereo imaging [4], tracking gloves [5], ultrasound [6]
- We propose a low-cost approach to build models that translate sEMG recordings to hand kinematics
- We use recurrent neural networks (RNNs) with Gaussian mixture model (GMM) to estimate hand kinematics

Training workflow

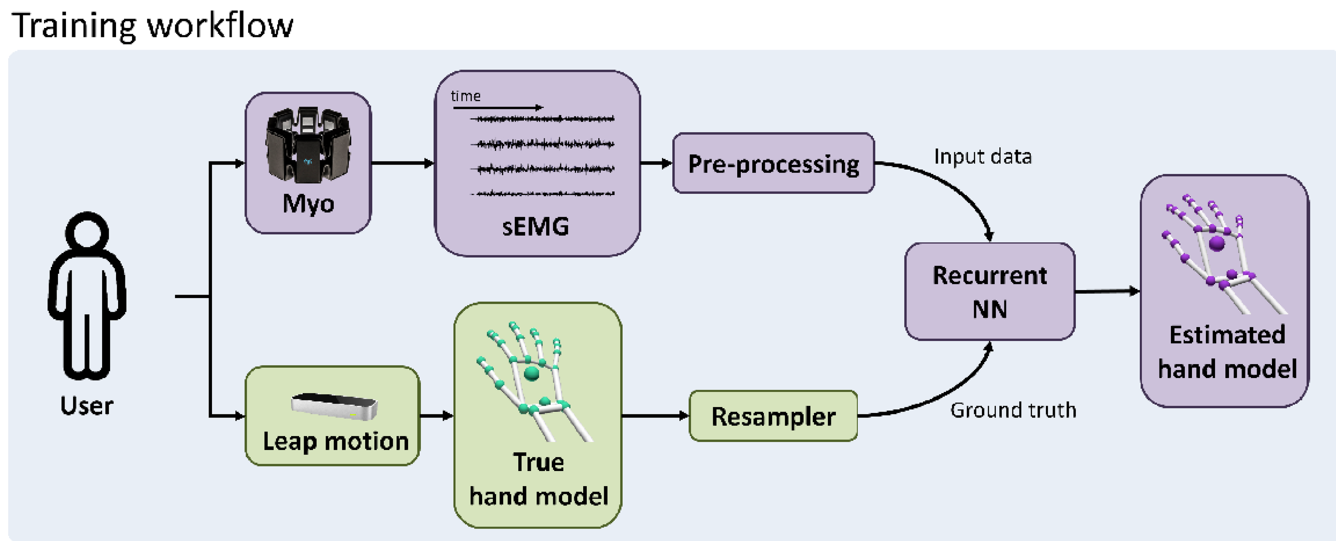


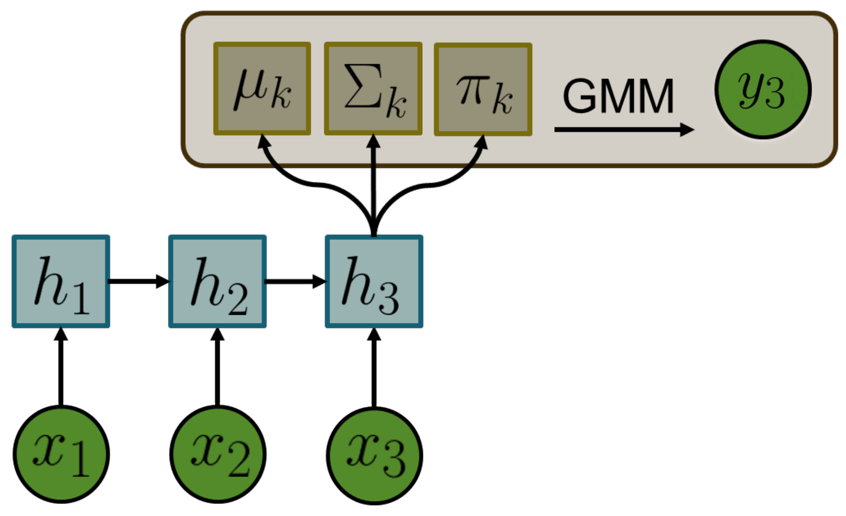
Figure 1: Data collection and training architecture

Regression with MDNs

- We use recurrent mixture density networks (RDNs), composed of long short-term memory (LSTM) with output layers parametrizing GMM [7, 8]

$$p(\mathbf{y}_n|\mathbf{x}_{\le n}) = p(\mathbf{y}_n|\mathbf{x}_{<n}, \mathbf{x}_n) \approx p(\mathbf{y}_n|\mathbf{h}_{n-1}, \mathbf{x}_n)$$
$$= \frac{1}{K}\sum_{k=1}^{K} \mathcal{N}(\mathbf{y}_n|\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)\pi_k,$$

where $\boldsymbol{\mu}_k := \boldsymbol{\mu}_k(\mathbf{h}_{n-1}, \mathbf{x}_n)$, $\boldsymbol{\Sigma}_k := \boldsymbol{\Sigma}_k(\mathbf{h}_{n-1}, \mathbf{x}_n)$, and $\pi_k := \pi_k(\mathbf{h}_{n-1}, \mathbf{x}_n)$ are outputs of the RNN



Data Collection and Training

- sEMG data is collected from the Myo [9] and muscle activation was estimated by computing mean absolute deviation (MAD) on a moving window: $x_{\mathrm{MAD}}(n) = \frac{1}{L}\sum_{k=n-L+1}^{n} |x(k) - m(k)|$
- Hand pose data were collected from the Leap motion and resampled to 200 Hz with the joint coordinates transformed to be relative with respect to the hand itself
- The 3D joint data (22 joints) were compressed with principal component analysis (PCA)

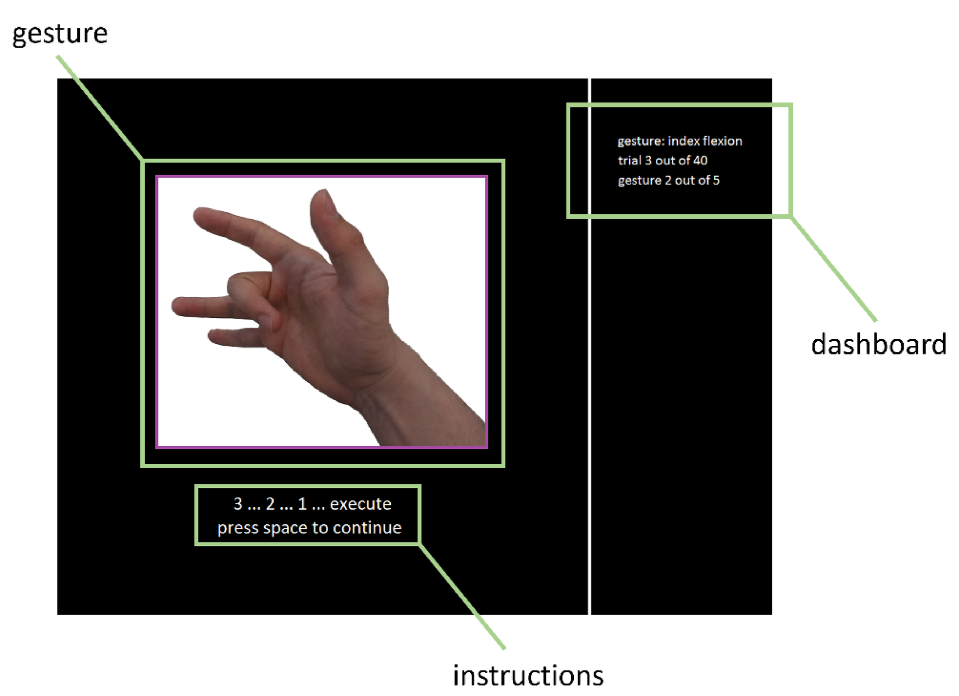


Figure 2: Data collection user interface

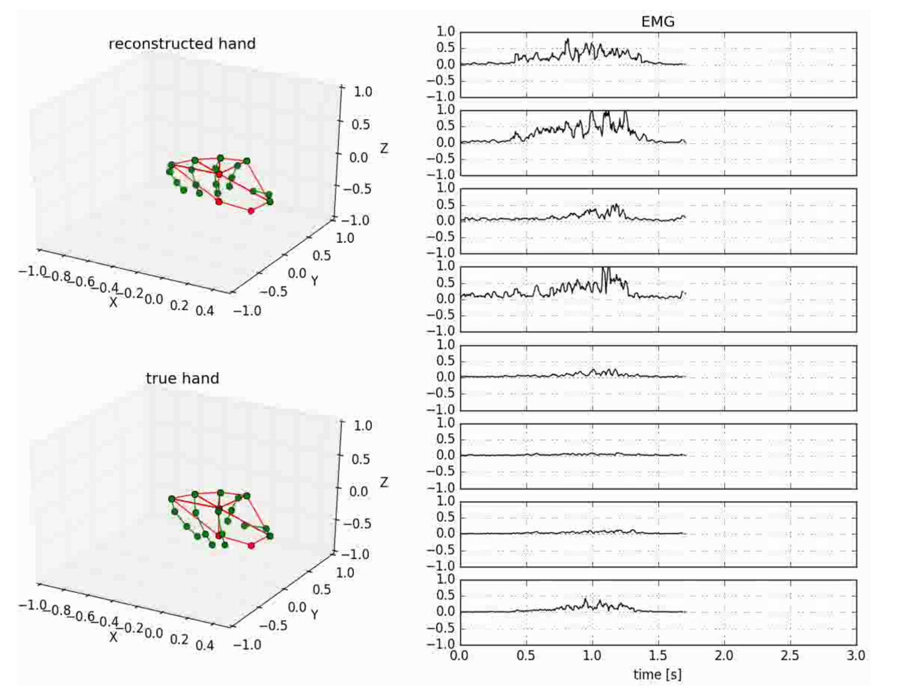
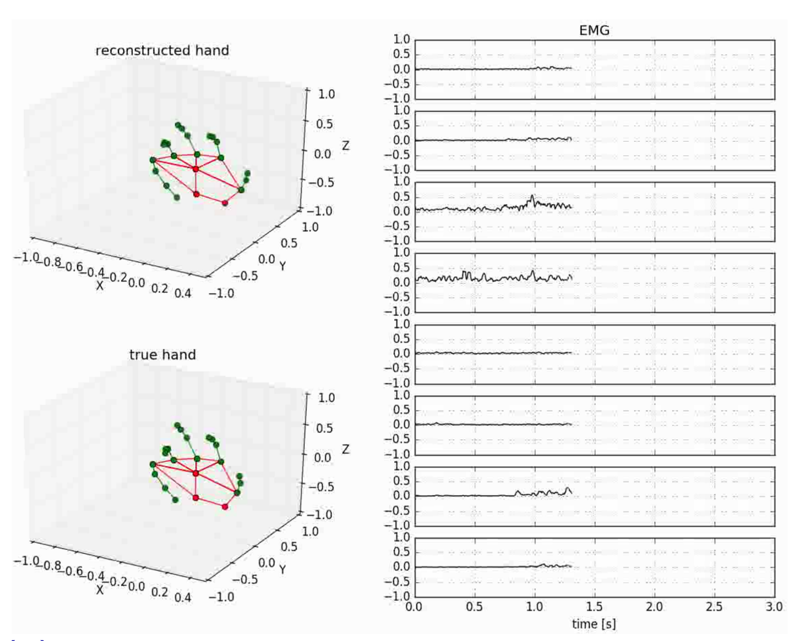


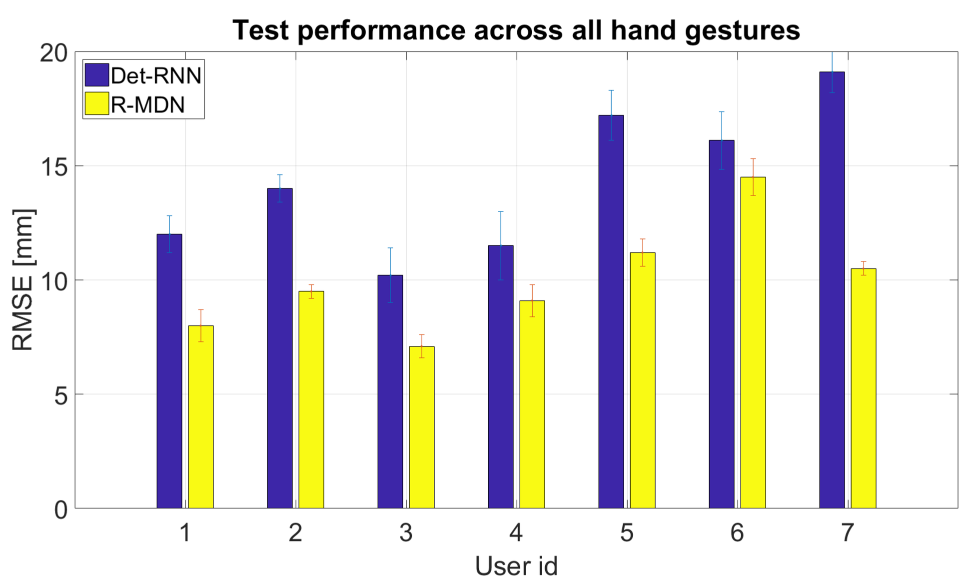
Figure 3: Example of experimental data: Power Grasp

Performance and Discussion

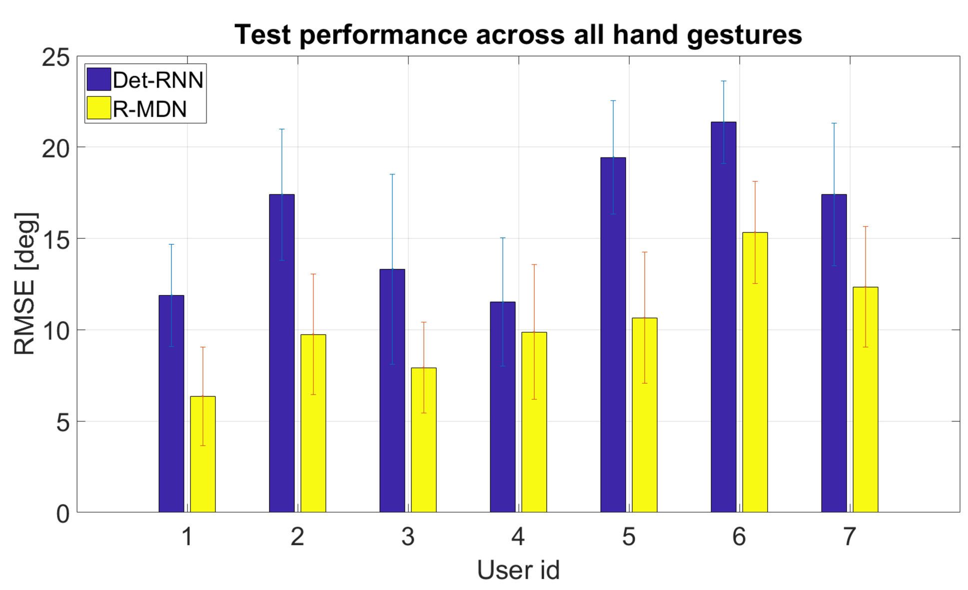
- 7 subjects were asked to perform the experiment with basic hand postures: flexion for each finger, resting state, and spherical power grasp
- 40 trials per hand posture were collected for each user (3 seconds plus 3 seconds for resting)
- Users were asked to perform the gesture starting from resting position
- Probabilistic RMDN outperforms deterministic RNN; root mean-square-error (RMSE) of 3.5 mm vs. 11.6 mm except thumb joints.



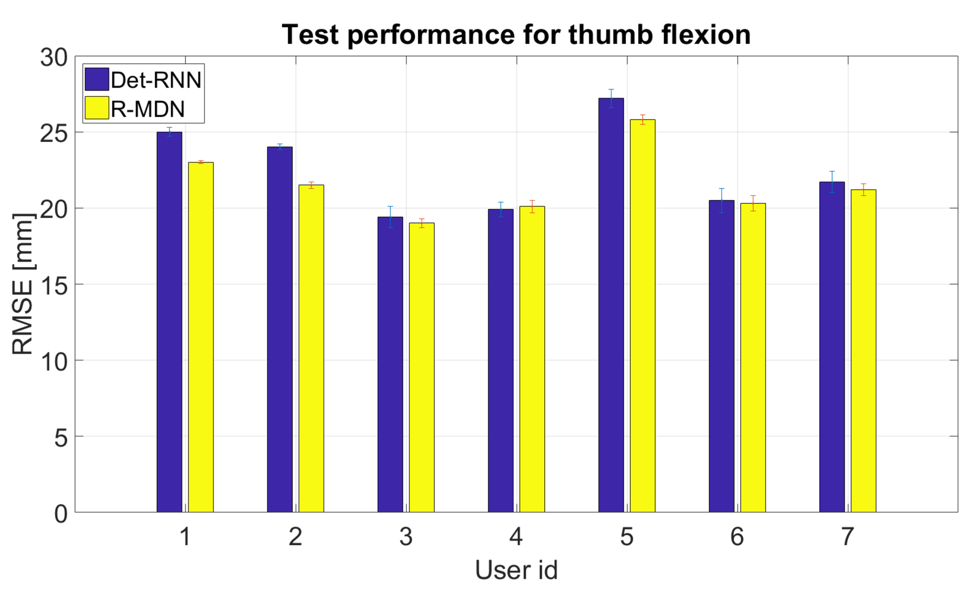
(a) Predicted & true pose with sEMG: Pinkie flexion



(b) RMSE of joint distances across all gestures



(c) RMSE of joint angles across all gestures



(d) RMSE of joint distances for thumb flexion

Figure 4: Performance of deterministic and MDN networks

Summary

- Our study shows successful reconstruction of finger movement from low-cost sEMG recordings
- RMDNs are shown to be powerful time-series models that can capture the hand kinematic variability
- We achieved RMSE of 3.5 mm except thumb joints, which was three-fold better than deterministic RNN

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