Rider posture-based authentication with few- shot learning for mobility scooters

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Motivation

Mobility scooters are crucial for people with mobility challenges, particularly seniors, yet there is a notable gap in research focused on enhancing their security in smart communities.

Traditional authentication methods, like physical keys and passwords, fall short for users with memories difficulties, necessitating innovative authentication solutions.

Despite the promise of deep learning in behavioral biometrics, current approaches are impractical for mobility scooters due to the unique demands of scooter riders for comfort and easy deployment.

Existing Solutions

Current biometric authentication solutions monitor the following:

Behavioral Characteristics

- **Gait**
- **Keystrokes**
- **Touch**
- Gestures
- Device Context

Physiological characteristics

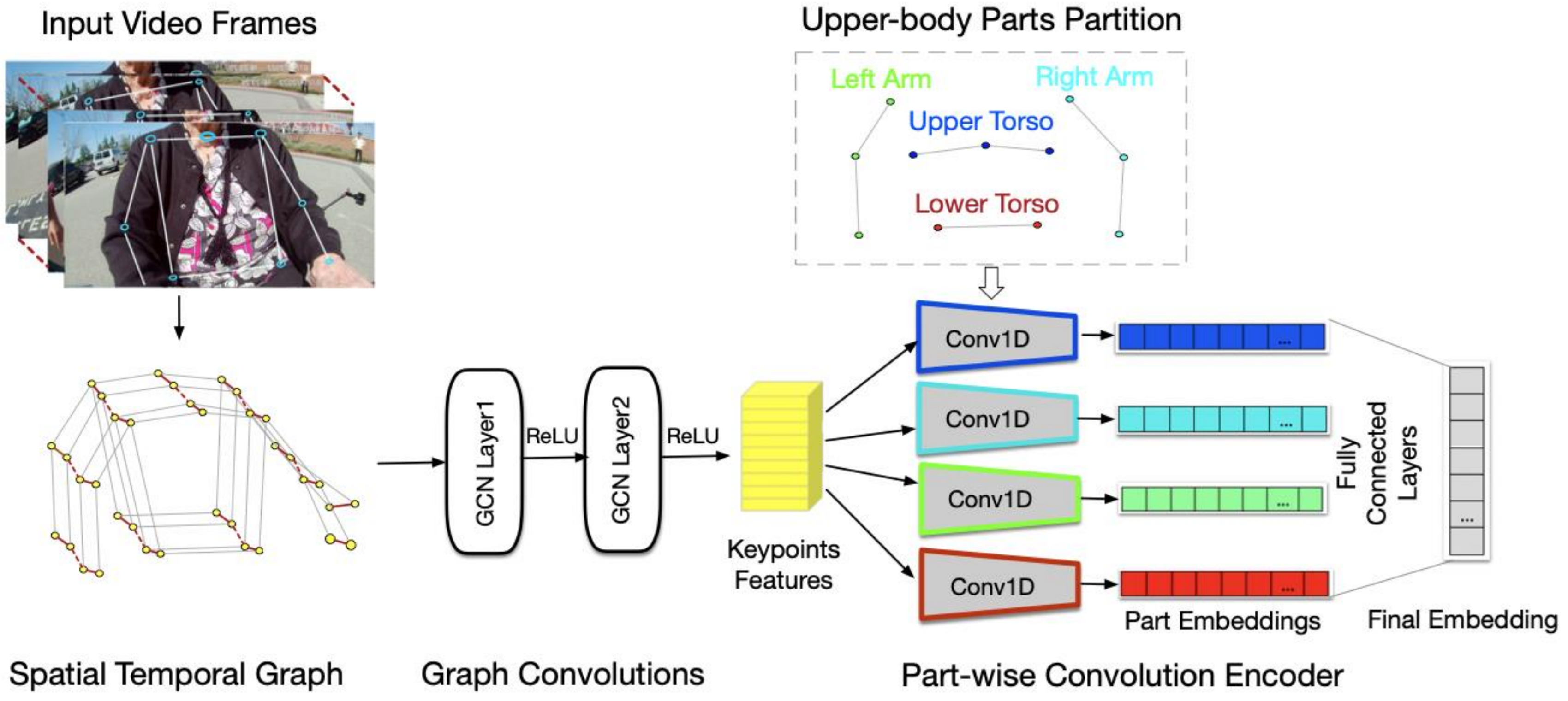
- **Pulse**
- Fingerprints
- **Face**
- Voice
- **EEG readings**

With **Bold** indicating the characteristic is a suitable choice for continuous authentication

Limitations of prior work:

- We strive to only use a user-facing camera
- Continuously recording a user's face is unnerving
  - Techniques that use a blurred sensor suffer in dynamic situations
- Prior posture-based authentication solutions suffer due to:
  - Scalability: must retrain the entire model to add a user or model per user
  - Deployment: involve expensive and custom sensors
  - Accuracy: only one prior group achieved lower than a 10% false rejection rate

Model Architecture



Data, Training, and Inference

We collected data from 42 users who performed 4 tasks testing different movement types while on the scooter

To train the embeddings model, we employ Triplet Metric Loss

$$L(x^a, x^p, x^n) = \max(||f(x^a) - f(x^p)||_2 - ||f(x^a) - f(x^n)||_2 + \alpha, 0)$$

To enroll in the authentication system, the user rides the scooter for 3 minutes, producing several riding embeddings encapsulating the user's riding patterns.

Every 4 seconds, we compare the current embedding to stored rider embeddings to make an authentication decision.

Age	Female	Male
18-25	4	30
26-60	2	2
>60	3	1
Total	9	33

Fig. 1: Participant #

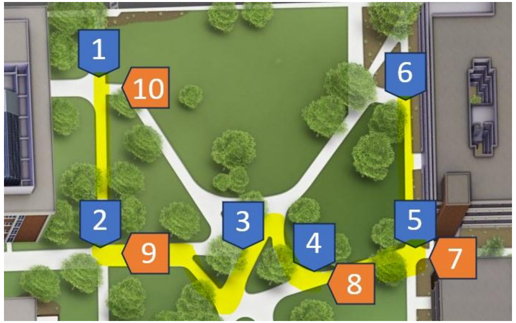


Fig. 2: Riding Route

Evaluation

We test two pose estimation models MediaPipe and MoveNet to generate the keypoint coordinates in our system and keep other components the same.

Pose Est.	**Enrollment Samples**				
	1	**5**	**10**	**20**	**40**
MoveNet	0.976	0.986	0.990	0.987	0.990
MediaPipe	0.981	0.896	0.962	0.960	0.964

Table 2: ROC AUC of the Authentication System

The results show that this system provides an accurate continuous authentication system for mobility scooter riders, and additional results showcase that the system is easy to deploy.

References

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