Driver Posture-based Continuous Authentication with Few-Shot Learning

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Abstract

Contemporary methods for authenticating mobility scooter users, such as physical keys and password-based security, are inadequate, particularly for seniors with memory issues. Our research introduces a novel continuous authentication system for mobility scooters, using few-shot learning, hierarchical processing, and contextual embedding to process rider posture data. This system offers rapid enrollment, easy deployment, and non-intrusive security. Additionally, we present the largest public dataset of such data to promote future work.

Introduction

- 1.7 million Americans use mobility scooters.
- New authentication systems applicable to scooters have trailed behind despite increasing connectivity.
- Current practices of user authentication via physical keys and traditional password-based one-time security mechanisms fall short in accommodating many users, such as those with issues recalling memory.
- In this work, we use drivers' posture data to perform continuous authentication on the mobility scooter, assuming there is a camera facing the driver.

Our system emphasizes:

Scalability Easily adds new users without needing to train a new model.	**Privacy-Awareness** Avoids using highly-sensitive data, such as the face.
Deployability Rather than complex sensor arrays, only uses a camera.	**Accuracy** Detects suspicious users with 95% accuracy in standard settings.

Data Collection

- We collect driving behavior data from 42 participants.
- The resultant dataset has over 10 hours of footage and over 1 million data points.
- 34 participants are between the age of 18 and 24, 3 between 24 and 65, and 5 are between 65 and 90.

Figure 1: Two of the scooters used for data collection.

Figure 2: Path riders drove during first section of driving.

Age	*Sex*	*ht*	*wt(lb)*	*Condition*	*Impairment*
87	F	5'8"	200	Neuropathy	neck, trunk
53	M	6'1"	182	Brain Injury	Lower extr.
85	F	5'6"	230	Sciatica	Left lower extr.
90	F	5'7"	156	Arthritis	Both hips
62	M	5'7"	180	back&shoulder	Left upper extr.

Table 1: Medical data of hospital patient volunteers.

References

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Approach

1. Extracting Posture Data:
   - The default model configuration makes an authentication decision based on a batch of 128 frames of torso data, which constitutes approximately 4 seconds of recording.
   - For each frame, a pose estimation model estimates 3D coordinates for each of 9 joints.

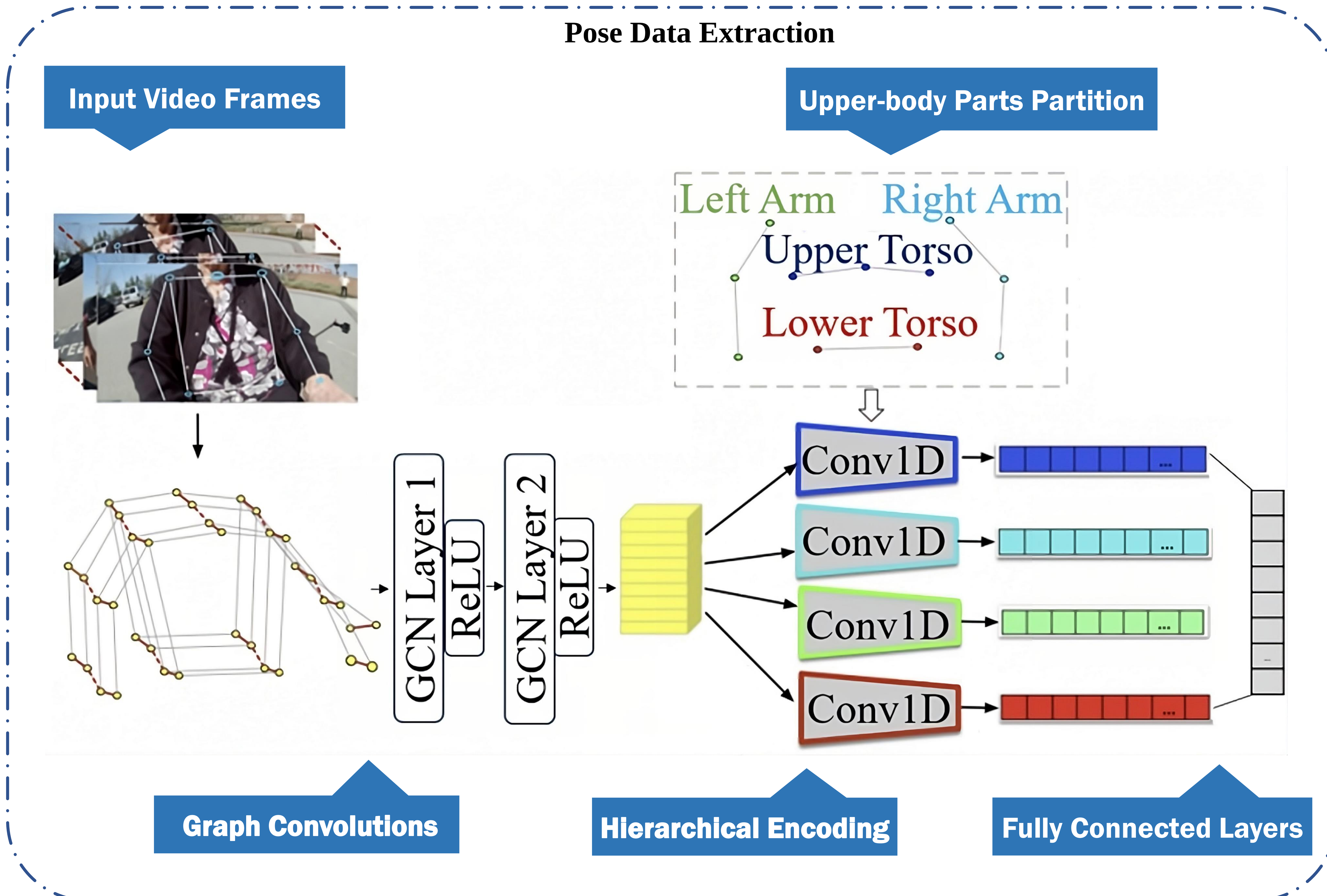

Figure 2: Authentication Process Overview

2. Model Inference:
   - Given time-series joint data, we construct a spatio-temporal graph of upper-body movement.
   - We then perform graph convolutions to produce more context-full joint embeddings.
   - With this enhanced key-point data, we perform hierarchical encoding with part-wise convolutional encoders to produce part embeddings.
   - We apply a fully-connected neural network on the part-embeddings to produce a final output.

3. Decision Procedure:
   - We then compute the distance between the embedding representing the current rider and the embeddings from the owner collected during enrollment.
   - Based on comparing this distance to a variable threshold, which users can set to maximize security or minimize false positives, we decide the validity of the rider.

Evaluation

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.

We test two pose estimation models MediaPipe and MoveNet (both from Google) to generate the key-point coordinates in our system and other components and experiment settings are kept the same. Table 2 illustrates the Area Under the Curve (AUC) metric for the ROC curve of the authentication system. The two systems both yield high accuracy using few enrollment samples. We also note the system based on MediaPipe has greater variability and is less accurate then when using MoveNet.

Conclusion

This works provides a continuous authentication system for mobility scooter riders. Our model leverages spatio-temporal graph convolutions before a hierarchical encoding structure to produce embeddings and is trained with Triplet Metric Loss. Experimental results based on real mobility scooter riders' data show that our system is easy to deploy and accurate.