Inertial-Measurement-Based Biometric Authentication of Handwritten Signature

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Introduction

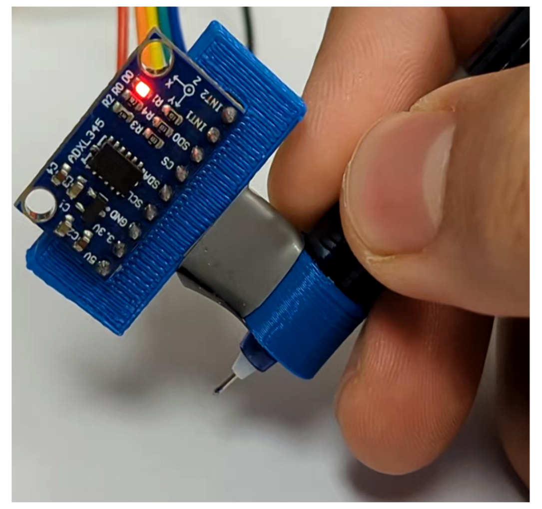
Increasing reliance on digital usage for personal, financial, medical, and policy information results in a greater demand for robust cybersecurity protection measures. This projects leverages the fact that the thoroughly trained process and motions of handwritten signatures is unique for every individual. Thus, a writing stylus that can authenticate its user via inertial signature detection is proposed, which classifies inertial measurement features for user authentication. Two triaxial accelerometers are mounted at each end of the stylus. Novel, manual spatiotemporal features relating to such metrics were proposed and a multi-layer perceptron was utilized for binary classification. Results of a preliminary user study are promising with overall accuracy of 95.7%, specificity of 100%, and recall rate of 90%.

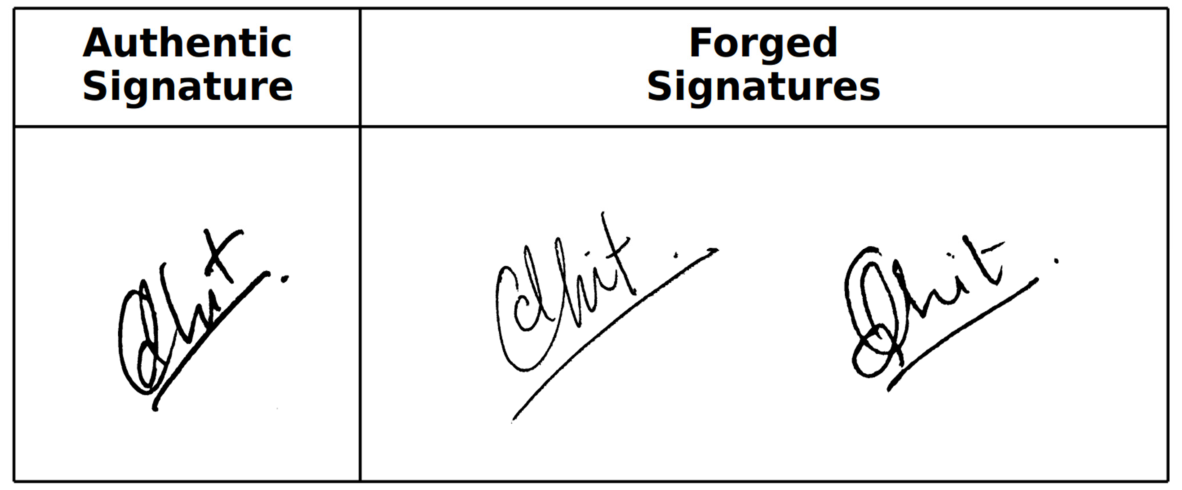
System Design

In this prototype design, two off-the-shelf accelerometers (ADXL 345) were used. These sensors were affixed near the two ends of the writing stylus using PLA mounts. A Raspberry Pi was used to facilitate data collection and storage from the sensorized writing stylus. The two accelerometers were connected to Raspberry Pi through Serial Peripheral Interface(SPI), thus sharing serial clock for synchronization – they were configured to collect samples at 1000Hz.

Methods

Three human subjects were recruited for a preliminary user study. Subject 0 performed their authentic signature while Subject 1 and Subject 2 attempted to forge Subject 0's signature. 50 trials from each subject were taken with each spanning 3 seconds, resulting in total of 50 true signatures and 100 forged, totaling 450 seconds worth of acceleration data.



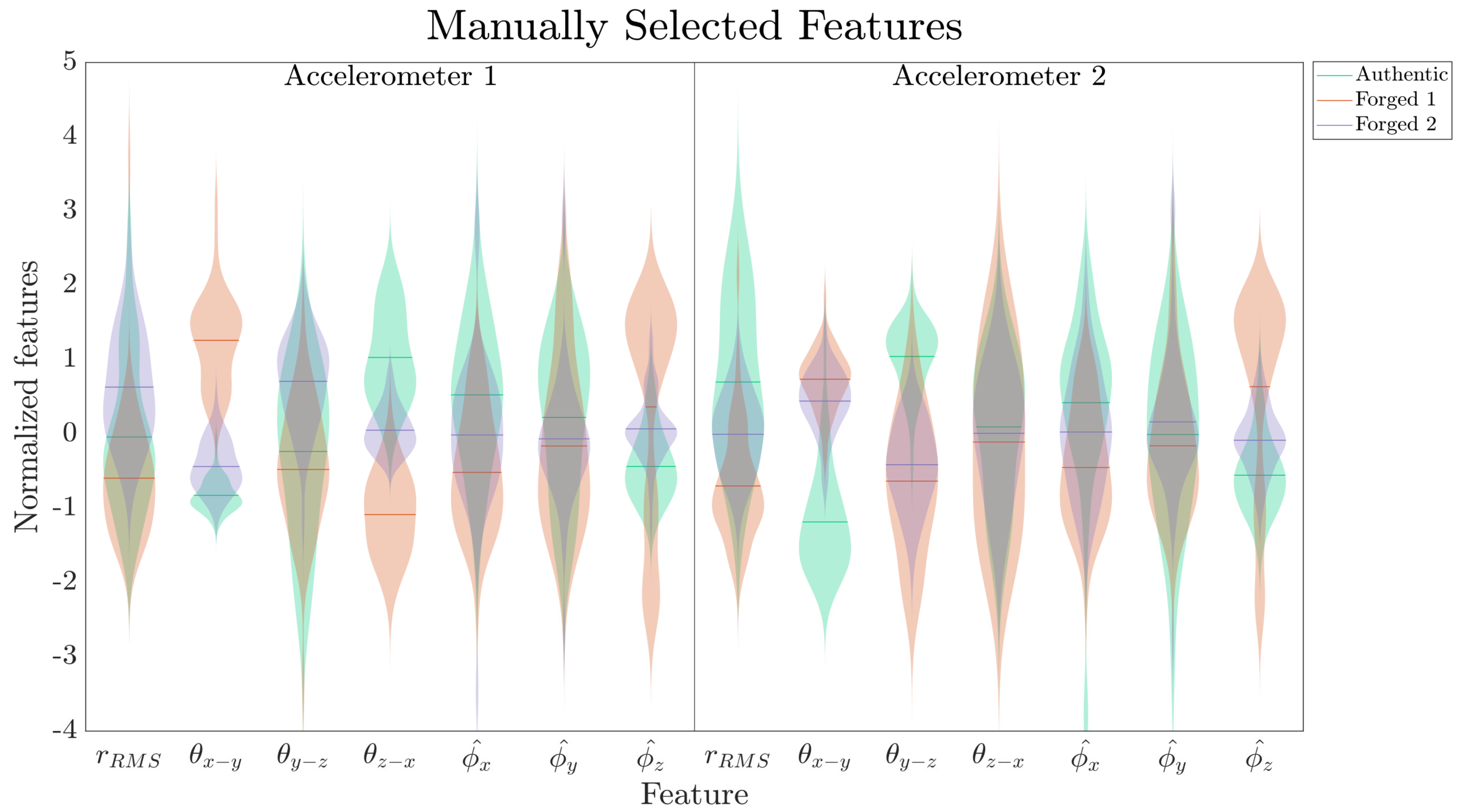


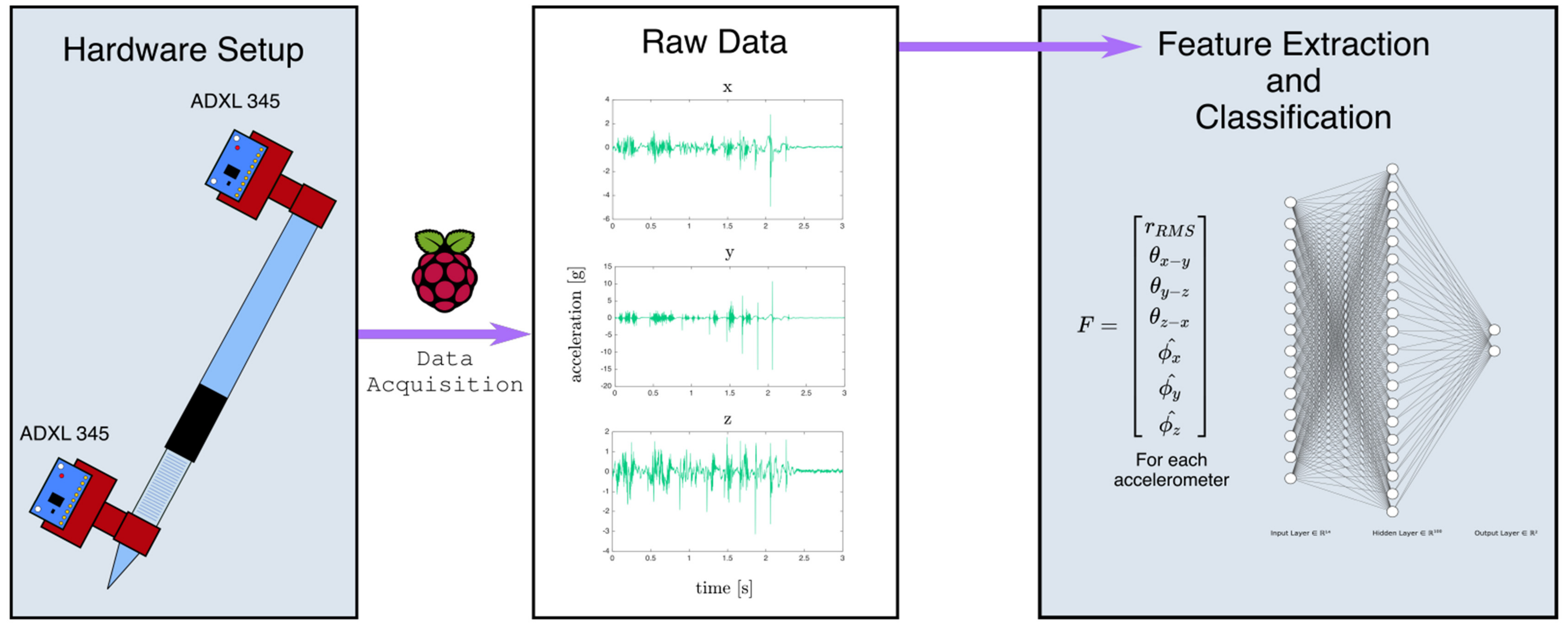
Feature Extraction

The features were designed with motivation to study energy distribution both along the spatial axes (r_{RMS}, θ_{i-j}) and the temporal distribution of energy ($\hat{\phi}_i$).

$$r_{RMS} = \sqrt{\frac{1}{N}\sum_t a_x^2(t)+a_y^2(t)+a_z^2(t)} \qquad \theta_{i-j} = \arctan\left(\frac{a_{iRMS}}{a_{jRMS}}\right) \qquad \hat{\phi}_i = \arg\left(\frac{1}{N}\sum_t a_i(t)\cdot\exp\left(2\pi\frac{t}{T}\right)\right)$$

Here, T is the total time of data collection per sample, N is the total number of data points per sample, i and j one of the 3 spatial dimensions, viz. x, y, or z.





Classification

For classification, a multilayer perceptron was trained with a single layer of 100 perceptrons. The 14 features served as an input to the classifier which yielded an output of vector with size two (forged vs. authentic). The network was trained to learn the authentic signature. 127 samples (40 authentic signature and 77 forged signature) were used for training while 23 samples (10 authentic signature and 13 forged signature) were used for testing, resulting in a roughly 85% to 15% split.

Results

Test Confusion Matrix

Output Class \ Target Class	0	1	
0	**13** 56.5% TN	**1** 4.3% FN	92.9% 7.1% **NPV**
1	**0** 0.0% FP	**9** 39.1% TP	100% 0.0% **Precision**
	100% 0.0% **Specificity**	90.0% 10.0% **Recall**	**95.7% 4.3%** **Accuracy**

Conclusion

In this paper, a proof of concept, preliminary study for signature authentication utilizing inertial measurements was conducted. By implementing a multilayer perceptron with 14 manually selected spatiotemporal features, an overall accuracy of 95.7% was achieved.