EE6563 Project Proposal
Footprint Recognition based on the Spatio-Temporal Features

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Abstract

Given present-day security concerns, many buildings have implemented robust authentication techniques. Aside from authentication to enter a building, applications such as border and airport security also administer identification. Therefore, many cities and companies provide technologies like CCTV or fingerprinting for authentication and verification. But each system has its own drawbacks. For example, due to the Covid-19 pandemic, most people wear a mask and avoid touching unnecessary surfaces. In this research, we work on a new biometric system called gait recognition. This system has some benefits in comparison to CCTV and fingerprint.

Keywords: Footprint recognition, Time series, pressure sensor

1. Introduction

Contemporary security identification has led to a plethora of biometric-based authentication systems. From palm readers at testing centers to facial recognition on smartphones, many systems are now used to regularly verify identities. These inherence-based systems are attractive in comparison to knowledge or possession-based methods of authentication because biometrics are highly unique, unforgettable, and far more difficult to steal than a password or swipe card.

Although biometric identification appears sophisticated when compared to something like physical keys, it does not come without its own share of caveats. For example, due to the ongoing Covid19 pandemic, many people wear masks when outside of their house, challenging most facial recognition systems. Additionally, biometrics that rely on touch, such as fingerprinting, raise safety concerns, as the scanner may become a vector for virus transmission. Despite these setbacks, given their merits and widespread deployment, biometric identification systems are unlikely to disappear.

One behavioral biometric that has gained recent success and is worth further consideration given current constraints is gait recognition. Usage of gait recognition has grown in the security industry in recent decades due to advances in deep learning. Singh et al. [1] categorized gait recognition into two main categories, vision-based and sensor-based. In vision-based approaches, cameras capture data of a person walking for the purpose of gait recognition. Sensor-based gait recognition is performed using either wear-

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able sensors which produce kinematic data, or floor sensors which produce kinetic data [2].

2. Datasets

This project uses two different datasets, UoM-Gait-Dataset and Stepscan. The UoM-Gait-Dataset obtained from iMAGiMAT [3] (an optical floor sensor). This sensor contains about 160 distributed plastic optical fibers (POFs) that indicate the foot pressure signals over time. Some studies like [4] use this dataset to construct an image for their research.

The second dataset that was used for this project is called the Stepscan dataset [5]. This dataset was obtained from high-resolution floor tiles that has recently introduced by Stepscan Technologies Inc.

Figure 1 indicates three frames from this dataset. This dataset consists of a spatial-temporal tensor, X, with dimensions $S \times T \times H \times W$ where S represents the number of samples. T is the number of temporal observations or video frames, H and W are the dimension of the image in pixels. Moreover, both datasets have some information about walking speeds.

This project aims to find some temporal features from the datasets to construct a classifier for verification duty. The nature of data in the first dataset is time series, whereas Stepscan is an image base dataset. There are several methods to convert video or image to the time series data.

Chen et al. in [6] used contour width for defining a one-dimensional signal. They utilized some morphological operations on the background-subtracted silhouette image to extract the outer contour. Afterwards, according to the contour width of each image row, a one-dimensional signal was generated.

Another method could be that the pixel values in each frame are plot over time. Therefore, the $H * W$ time-series will produce for each sample.

In the final method, some spatial features are extracted from each frame (e.g. centroid and maximum pressure in each image). Afterwards, we track these values over time (next frames). As a result, 3D videos with size $T \times H \times W$ convert to the four time-series data. Costilla-Reyes et al. utilized this method to combine the output of 160 distributed POFs [7].

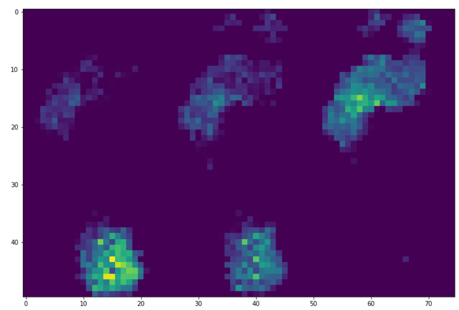


Figure 1: Different frames of footprint video in Stepscan dataset.

In this research, the last method was applied to produce time-series data. Figure 2 indicates the time series extracted from the Stepscan dataset. The spatial features extracted in each frame were maximum pressure (figure 2a), the center of pressure (COP) (figures 2d and 2c), and the average pressure (figure 2b).

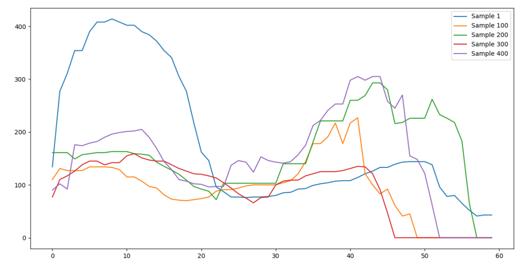
3. Literature Review

DARPA, the Defense Advanced Research Projects Agency of the USA, started to research gait recognition by vision data in the early 2000s [2]. Besides vision data [6], some studies have instead used accelerometry from smartphones [8], audio [9], and underfoot pressures data [10].

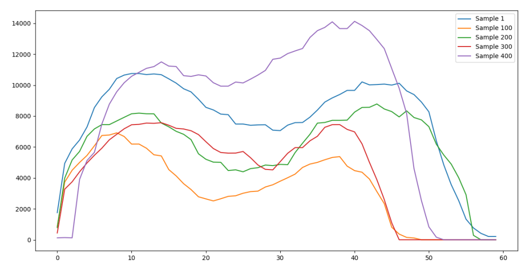
Addlesee in [11] used a new sensor (Active floor) for the first investigations into footprint recognition. This sensor was a square carpet tile maintained at the corners by some load cells and supplied the Ground Reaction Forces (GRFs). Orr and Abowd [12] extracted ten temporal features from the GRFs curve.

Moustakidis et al. [13] extracted temporal features from the wavelet decomposition of GRFs and then applied a kernel-based support vector machine. These studies have limitations in terms of the small sample sizes used for classification (e.g., 15 [12], 10 [13], and 15 [14]), and moderate classification rates ($CR < 90\%$).

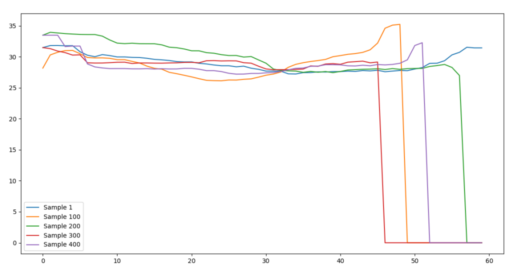
Pataky in [15] could achieve a 99.6% classification rate in a 104-participant dataset. This result was



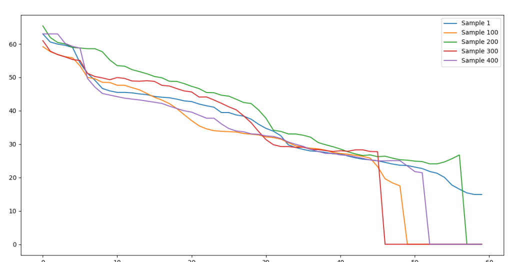
(a) The maximum pressure in each frame



(b) The average pressure in each frame



(c) The x position in the center of pressure (COP) in each frame



(d) The y position in the center of pressure (COP) in each frame

Figure 2: The time series extracted from the Stepscan dataset based on four spatial features. The horizontal axis indicates the frame number.

based on spatial alignment and automated dimensionality reduction. He used a template image that was made in [16]. Pataky named this template the Munster-104 template.

In 2015, Cantoral-Ceballos [3] introduced an intelligent carpet system. This carpet system (iMAGiMAT) worked based on the deformation of 116 distributed POFs. So that applying pressure to this system would change the intensity of the transmitted light. Thus the nature of the output of this sensor is time-series data.

Costilla-Reyes et al. [17] extracted five features directly from raw data of the iMAGiMAT sensor. They implemented 14 various machine learning methods for classification. The best result belonged to the Random Forest model with a validation score of $90.84 \pm 2.46\%$.

Later, they in [7] used an end-to-end convolutional neural network to extract Spatio-temporal features automatically. This technique increased their score by about 7 percent.

Barandas et al. in [18] introduced a Python package entitled Time Series Feature Extraction Library (TSFEL). This Python package could compute more than 60 different features from the time-series data.

4. Constraints

The constraints in this project could fall into two groups. The first constraint is related to the limitation on laboratory conditions [2]. In real-world circumstances, many situations such as walking speed, clothing, footwear, and load carriage could affect our results, whereas our datasets could cover some of these real-world conditions. For example, except for the walking speed and footwear, both datasets do not have useful information for other real-world situations. Consequently, our results are optimistically biased. Table 1 indicates some inhibiting factors.

Another significant limitation in the Stepscan dataset is the lack of relative footprint location. The dataset included only aligned and segmented footprint images. The location of samples concerning each other is unknown. This information could play a significant role in predicting the location of future footsteps.

5. Proposed Work

There are two modes for footprint recognition or generally in the biometric system: verification or identification mode [19]. In verification mode, the biometric system use for accessing buildings or data. In other words, the system compares the claimed person with its dataset to determine whether or not the claim is valid. These systems consume less processing power and time consumption [19].

This project will focus on verification. Since each participant has multiple samples in our dataset, we hope to find some temporal features. These features help us to construct a classifier which can discriminate between our dataset's various participants. Since both datasets contain various walking speeds, it would be a good idea to find a classifier based on the participants' speeds.

In recent years, improving the computational process of computers and other benefits of Deep Neural Networks (DNN) causes many researchers (like [20] and [7]) to move towards DNN for the classification of time series data. Therefore, these algorithms will review in this project.

Having spatial features along with temporal information give us a freedom to select and combine many classifiers in the pipeline to increase our accuracy. We also plan to use some techniques learned in time-series analysis course hopefully elicit some useful features for future works.

Furthermore, this research will employ two available datasets (UoM-Gait-Dataset and Stepscan), and will be implemented in python. The source codes are available on the GitHub repository [21].

Table 1: Some inhibiting factors in gait recognition.

	Inhibit Factors
1	Footwear
2	clothing
3	Injury
4	Muscle development
5	Fatigue
6	Age
7	Load carriage
8	Walking speed

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