

Biometric Identification Using Gait Analysis by Deep Learning

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ABSTRACT: Traditionally, identification has been done on human characteristics like fingerprint, voice, face-id, and iris scan. Individuals typically feel that they'll determine a well-known person after merely recognizing the means that the person walks. This walking pattern of the person is termed GAIT. This GAIT is often used for the event of a system that uses Gait Parameters kind of biometric authentication. The system is meant in such some way that it focuses on simple usage, utility, and measurability. The project can eliminate the need for someone to manually build entry into the biometric identification system that uses conventional ways like fingerprint, voice, face-id, and iris scan for identification. The project that may be supported by supervised learning will acknowledge someone from the Gait features. The project is often used for biometric recognition as well as security purpose.

KEYWORDS: Machine Learning, Deep Learning, Artificial Intelligence, Biometric Identification, Gait Analysis, Gait Cycle, Human Gait.

I. INTRODUCTION

Biometric Gait Analysis has demonstrated potential promises as an alternative or complementary identifier for use in human recognition systems. There are several analysis techniques for human gait. Among these techniques are visual approaches involving cameras, which can capture different angles of gait from a distance, and sensor approaches, which collect information about gait while in contact with the subject being analyzed.

This being a research-oriented project we have tried to imbibe the knowledge with respect to gait and machine learning and will demonstrate via the application of powerful machine learning techniques and the levels of gait recognition performance we might hope to achieve using a sensor-based approach for demonstration. [1].

II. REVIEW OF LITERATURE

We define gait to be the coordinated, cyclic mixture of actions that result in human locomotion. The moves are coordinated inside the experience that they ought to occur with a specific temporal pattern for the gait to arise. The moves in a gait repeat as a walker cycles among steps with alternating feet. It is each the coordinated and cyclic nature of the movement that makes gait a unique phenomenon.

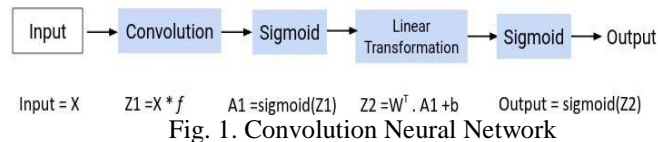
Therefore, we tend to define gait recognition to be the popularity of some salient property, e.g., identity, sort of walk, or pathology, supported the coordinated, cyclic motions that end in human locomotion. Within the case of biometric gait recognition, the salient property is identity. We tend to create the excellence between gait recognition and what we decision similar gait recognition during which a salient property is recognized supported options non-heritable whereas a subject matter is walking, however the options aren't inherently a part of the gait. Let's say, skeletal dimensions could also be measured throughout gait and accustomed acknowledge a personal. However, skeletal dimensions could also be measured different ways in which, and are thus not a property of the gait. [2]

A Convolutional Neural Network (ConvNet/CNN) is a Deep learning knowledge of set of rules that may take an input photo, assign importance (learnable weights and biases) to numerous components/objects within the picture and have the ability to distinguish one from the alternative. The pre-processing required in a ConvNet is a whole lot lower compared to different category algorithms. At the same time as in primitive techniques filters are hand-engineered, with sufficient education, ConvNets have the capacity to learn these filters/traits.

The Gait process is a way to identify men. In a single individual, it starts when one foot is in contact with the ground

and ends when that foot is in contact with the ground again. As such, it relies heavily on human identity and recognition machine learning and is an effective biometric identification technique.

Transfer learning has the power to utilize existing data from the supply learner within the target task. It is a preferred approach in deep learning wherever pre-trained models are used because the start line on laptop vision and linguistic communication process tasks given the immense reckon and time resources needed to develop neural network models on these issues and from the massive jumps in ability that they supply on connected problems.



Residual Neural Network(RNN) are a sort of Neural Network where the output from previous step are fed as input to the present step. In conventional neural networks, all the inputs and outputs are freelance of every alternative, however in cases like once it's needed to predict subsequent word of a sentence, the previous words are needed and thus there's a necessity to recollect the previous words. Thus, RNN came, which resolved this issue with the assistance of a Hidden Layer. The most and most vital feature of RNN is Hidden state, that remembers some info a few sequences.

Formula for calculating current state:

$$h_t = f(h_{t-1}, X_t) \text{ Where:}$$

h_t – current state

h_{t-1} – previous state X_t – input state

Formula for applying Activation function(tanh): $h_t = \tanh(W_{hh}h_{t-1} + W_{xh}X_t)$

Where:

W_{hh} – weight at recurrent neuron W_{xh} – weight at input neuron

Formula for calculating output:

$$y_t = W_{hy}h_t \text{ Where:}$$

y_t – output

W_{hy} – weight at output layer [2].

III. SYSTEM DESIGN

From the below block diagram (Fig.2) we can observe that firstly, there is an input video which is taken for training and testing purpose. This input video can vary upon the resolution and background. This video must contain the subject's full body ie:- Head to Toe such that the gait cycle parameters can be obtained correctly.

Next block is the Gait Recognition System which does the main job of biometric identification using gait analysis. Right from the initial training to the final testing and identification result this block takes care of everything.

The detailed workflow of Gait Recognition System block has been mentioned in figure 3 wherein the actual mechanism of this block is explained.

The storage block is connected with the gait recognition system block because storage of unique gait parameters is done in parallel and its an essential part of the system design.

The output block basically displays the result which identifies the person and shows the error percentage of each gait parameter.

This project is designed based on the following block diagram mentioned below-

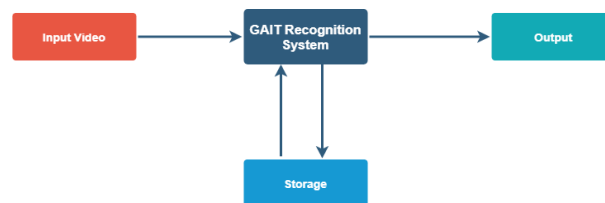


Fig. 2. Generalised System Architecture

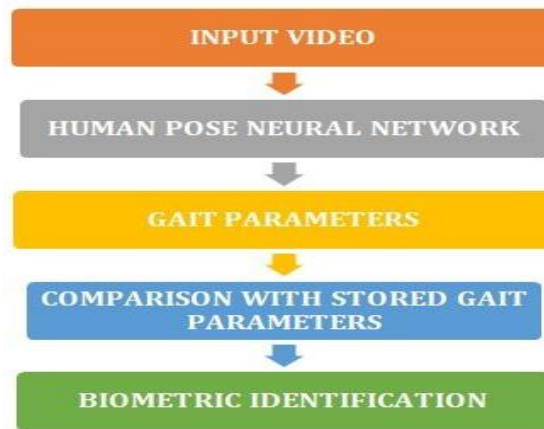


Fig. 3. The Flowchart of System

MPII Human pose dataset could be a state of the art benchmark for analysis of articulated human pose estimation. The dataset includes around 25 thousand pictures containing over 40 thousand individuals with annotated body joints. The photographs were consistently collected using a longtime taxonomy of each day human activities. Overall the dataset covers 410 human activities and every image is supplied with associate activity label. every image was extracted from a YouTube video and supplied with preceding and following un-annotated frames. additionally, for the check set we tend to obtained richer annotations as well as piece occlusions and 3D body part and head orientations. We propose a partitioning and labeling formulation of a collection of body-part hypotheses generated with CNN- based part detectors. Our formulation, associate instance of an whole number linear program, implicitly performs non-maximum suppression on the set of half candidates and teams them to create configurations of body elements respecting geometric and look constraints. Experiments on four completely different datasets demonstrate progressive results for each single person and multi-person cause estimation. [3]

Probabilities of the following human gait parameters which are obtained from this neural network as output are as follows:

- Right Knee
- Left Hip
- Right Wrist
- Left Knee
- Right Wrist
- Left Hip
- Pelvis
- Head

We have used a transfer learning approach. during this, we’ve imported the network ‘Human pose NN’ that is made on the InceptionResnetV2. we’ve imported the checkpoint file of the network. The checkpoint file is a binary file that contains all the values of the weights, biases, gradients and every one the opposite variables saved. Then we have a tendency to restore this stop file to get values of the weights, biases, gradients. Now, we have a tendency to use our pictures to coach the neural network supported these variables. Deep learning models are representative of what’s conjointly called inductive learning. the target for inductive-learning algorithms is to infer a mapping from a group of coaching examples.

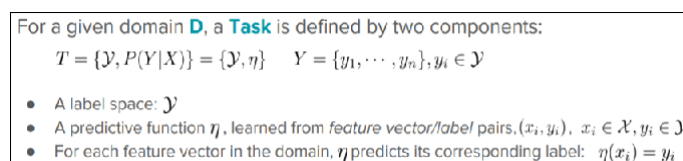


Fig. 4. Mathematics of Transfer Learning [4]



Download

MPII Human Pose Dataset, Version 1.0
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 Licensed under the Simplified BSD License [see [bsd.txt](#)]

We are making the annotations and the corresponding code freely available for research purposes. Commercial use is not allowed due to the fact that the authors do not have the copyright for the images themselves.

You can download the images and annotations from the MPII Human Pose benchmark here:

- ⊗ [Images \(12.9 GB\)](#)
- ⊗ [Annotations \(12.5 MB\)](#)

Below you can download short videos including preceding and following frames for each image. The videos are split for download into 25 batches ~17 GB each:

- ⊗ [Batch 1](#) ⊗ [Batch 2](#) ⊗ [Batch 3](#) ⊗ [Batch 4](#) ⊗ [Batch 5](#)
- ⊗ [Batch 6](#) ⊗ [Batch 7](#) ⊗ [Batch 8](#) ⊗ [Batch 9](#) ⊗ [Batch 10](#)
- ⊗ [Batch 11](#) ⊗ [Batch 12](#) ⊗ [Batch 13](#) ⊗ [Batch 14](#) ⊗ [Batch 15](#)
- ⊗ [Batch 16](#) ⊗ [Batch 17](#) ⊗ [Batch 18](#) ⊗ [Batch 19](#) ⊗ [Batch 20](#)
- ⊗ [Batch 21](#) ⊗ [Batch 22](#) ⊗ [Batch 23](#) ⊗ [Batch 24](#) ⊗ [Batch 25](#)
- ⊗ [Image - video mapping \(239 KB\)](#)

Fig. 5. Human Pose Dataset [3]

Inception-ResNet-v2, a convolution neural network (CNN) that achieves a brand new state of the art in terms of accuracy on the ILSVRC image classification benchmark. Very deep convolutional networks are central to the biggest advances in image recognition performance in recent years. One example is that the origination design that has been shown to attain excellent performance at comparatively low procedure value. This raises the question of whether or not there is any profit in combining the origination design with residual connections. Here we have a tendency to offer clear empirical proof that coaching with residual connections accelerates the training of origination networks considerably. [5]

We use the inception resnet to get the probabilities estimate of the joints. The input to the inception resnet is a 4-dimensional tensor of the image. Inception Resnet gives us two values:logit(probability) and end points(the set of end points from the inception model). These values are further used to let us estimate the joints.

IV. IMPLEMENTATION

We have executed a brand new approach whereby the system takes a video of an individual walking (in multiple directions) that is taken for training. we tend to then take the video and generate the frames of the video. Inception Resnet needs a 4D tensor as associate input. The output of the tensor is the possibilities of the joints. The neural network to estimate joints is predicated on the inception-resnet-v2. We tend to train the network till the required accuracy is achieved and so store the desired weights within the variety of checkpoints. The checkpoint file file could be a computer file that contains all the values of the weights, biases, gradients and every one the opposite variables saved. Then we tend to restore this stop file to get values of the weights, biases, gradients. Now, we tend to use our pictures to get the probabilities and store them.

For identification purpose (Testing Phase), we use the ready checkpoint file. We give our images as an input to the inception resnet, and generate the probabilities. The test probabilities are compared with trained probabilities to generate error. The person used for identification with the least error with corresponding data is recognized.

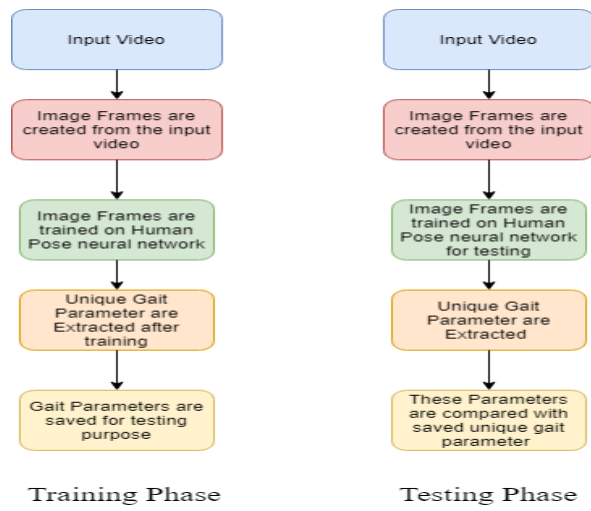


Fig. 6. Training & Testing Phases

V. RESULTS

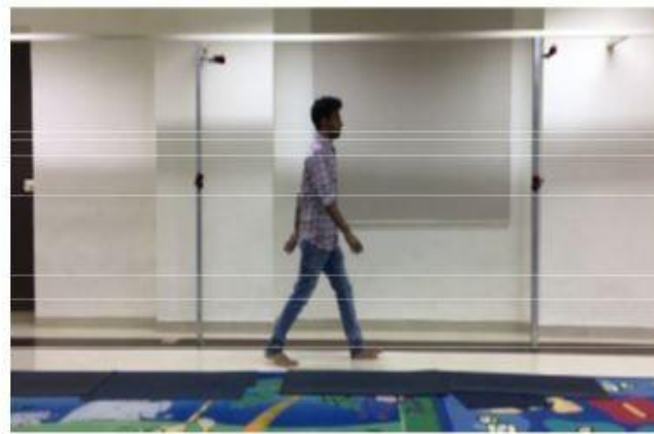


Fig. 7. Input Video Sequence Frame [7]

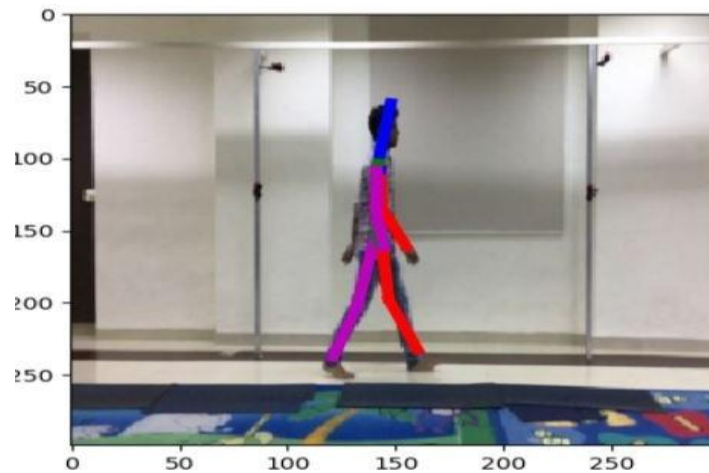


Fig. 8. Human Pose Generation [7]



Fig 9 : Output of Testing Phase

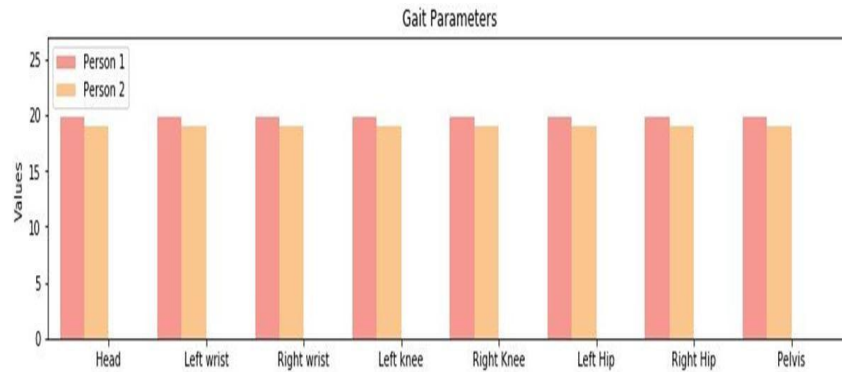


Fig. 10. Resultant Graph showing the comparison of each Gait Parameter

VI. CONCLUSION & FUTURE WORK

Extension of this project will be to implement it on real time continuous input from multiple cameras at a single time of reference. This will ensure 24x7 security and can be used in real world surveillance systems in various organizations. Bank vaults, Nuclear reactors, Reserve Banks, Research labs, Military confidential areas are major application areas which require high level access control systems. Gait data of dangerous criminals can be recorded and used in real time CCTV systems to detect them and alert the concerned authorities. [6]

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