CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION TO BIOMETRIC AUTHENTICATION

Biometric authentication refers to security processes that verify a user's identity through unique biological traits such as retinas, irises, voices, facial characteristics, and fingerprints. Biometric authentication systems store this biometric data in order to verify a user's identity when that user accesses their account. Because this data is unique to individual users, biometric authentication is generally more secure.

On one side of the authentication challenge are users who demand speed and convenience and do not want to have to remember numerous passwords or make their way through a complex login or verification process every time they access private-access information or services. On the other hand, security requirements are quickly evolving to demand a rigorous approach to authentication.

Traditional methods of authentication such as the traditional username and password, knowledge-based authentication and SMS-based two-factor authentication have fallen out of favour due to a variety of security vulnerabilities ranging from account takeover to phishing to social engineering.

Authentication is the process of determining whether someone or something is, in fact, who or what it declares itself to be. Since the fraud landscape is evolving quickly, network administrators are facing plenty of challenges and have had to start implementing more sophisticated methods beyond multi-factor authentication. Some common types of biometric authentication include:

- Fingerprint Scanners
- Retina and Iris Recognition
- Voice Recognition
- Facial Recognition
- Liveliness Detection

Biometric systems work by comparing two sets of biometric data: the first one is pre-set by the owner of the device, while the second one belongs to a device visitor. The important thing to note is that the match between the two data sets has to be nearly identical but not exactly identical. This is because it's close to impossible for biometric information to match 100 percent.

1.2 REGULAR BIOMETRIC AUTHENTICATION - DOWNSIDES

While there are many advantages to common methods of biometric authentication, there are some disadvantages to it in the modern day and age, especially considering the latest restrictions imposed by the pandemic since the year 2020. Some of these disadvantages are as follows:

- **Inconvenient for Situations where User Cooperation is Not Available:** For methods such as retinal scan and fingerprinting, we need the users to cooperate and have perfect conditions for the scan to be successful, as they need to be in a perfect position for the scanning. This becomes inconvenient for cases where quicker authentication is required.
- **Closer Human Contact is Required:** Since social distancing has become a requirement in order to curb the pandemic, biometric authentication measures that involve closer human contact or physical contact become riskier. This increases the requirement for a more contactless method for biometric authentication. Some methods such as facial recognition require people to not wear masks, which is also a risk factor.

1.3 INTRODUCTION TO GAIT RECOGNITION

Gait is a biometric trait that depicts and measures how people move. Over the decades, gait analysis has been successfully used in different domains, including biometrics and posture analysis for healthcare applications. It has also been used in human psychology where gait analysis using point lights employed for recognition of emotional patterns. The same idea was extended and ultimately resulted in the development of gait signatures through which the identification of individuals can be performed.

In the early days of gait recognition, the focus was to identify and classify the different movement patterns such as walking, jogging, and climbing. Gradually, the focus shifted towards human identification and has become an active area of research. As compared to other biometric traits such as fingerprint and iris, gait recognition can work without the cooperation of a person. Moreover, it can work without interfering with a person’s activity. This makes gait more suitable for different real-time applications like surveillance and long-distance security

Gait recognition is one of the most important biometric technologies and has been applied in many fields. Recent gait recognition frameworks represent each gait frame by descriptors extracted from either global appearances or local regions of humans. However, the representations based on global information often neglect the details of the gait frame, while local region based descriptors cannot capture the relations among neighbouring regions, thus reducing their discriminative tendencies.

1.4 SCOPE AND BENEFITS OF GAIT RECOGNITION

Human gait recognition using the model-free approaches can be done through the analysis of moving shape and motion of the subject's body. The benefit of this approach is that the recognition can be performed at large distance with sufficiently low-resolution images. This approach is very simple and intuitive to extract gait signatures from the gait frames. This model-free approach may be addressed from different viewpoint.

The model-free gait recognition techniques are not limited to background subtracted images where human silhouette from the static background is identified by measurement of silhouette shape and motion. It has been observed that original textured images, key frame analysis, stereo vision using depth sensor imaging, content-based image retrieval on still images using Kinect device were also explored to extract gait features. Below are the benefits of Gait Recognition:

- **Non-invasive Biometric Recognition Method:** Since physical contact for the user is not required in order to perform gait recognition, this method of biometric authentication is a very useful non-invasive method. Especially given the restrictions caused by the mandated social distancing, the Gait Recognition method can be conducted while keeping in mind the necessary precautions, which is a big requirement today.
- **User Monitoring Does Not Require their Cooperation:** Since this method does not require the explicit consent and cooperation of the user, it can be conducted smoothly and without any hassle, as the user does not need to stand in proper positions in order to be authenticated, thereby increasing the success rate of such a method of biometric authentication.
- Gait recognition technology is less «touchy-feely» than other biometric verification systems such as retinal scans or fingerprints. Thus, it is non-invasive and can be applied without user consent. Moreover, the success rate of this technology is high – the error rate is only 0.7%.

1.5 SCIENCE BEHIND GAIT RECOGNITION AND METHODS USED

Gait recognition biometrics is the area of study in which human gait is taken as a biometric characteristic to uniquely identify individuals. Human beings have natural ability to recognize familiar people with their gait. Psychologists like Johansson G has shown that humans have ability to identify moving patterns in less than a second, which is not the case with static images showing a sequence of patterns.

This ability is developed over time by observing and learning to recognize patterns. On the other hand, a specific manner of walking is also developed as an individual age. It also keeps changing steadily with age. However, variations are slight when age is the only factor (except old age). It can also get affected by many other factors that we are going to discuss in a while. This coordinated, cyclic combination of movements that result in human locomotion is called gait. Each cycle of movements is repeated in the subsequent movements if physical or environmental conditions stay the same. These movements occur in a pattern and being dependent on many factors, they are considered to be unique for an individual. Not just manner of walking, but patterns of jogging, running and climbing stairs are also included in human gait.

A gait recognition system takes input from the data capture sub-system. It uses a capture device that can capture human motion. In a typical gait recognition setup, a video camera can be used for the purpose. It can also make use of on-body sensors, sensors on mobile phones or smart wearable devices, etc. to capture gait data. Radar based gait recognition systems are also being worked upon.

As is the case with other biometric systems, efficiency of a human gait recognition system depends a lot on the recognition algorithm used. A gait recognition system may take inputs from multiple capture devices like video camera, sensors, wearables, etc. How efficiently the system can make use of this raw data depends on the efficiency of the recognition algorithm. Typically, the processes performed in a gait recognition system are as follows.

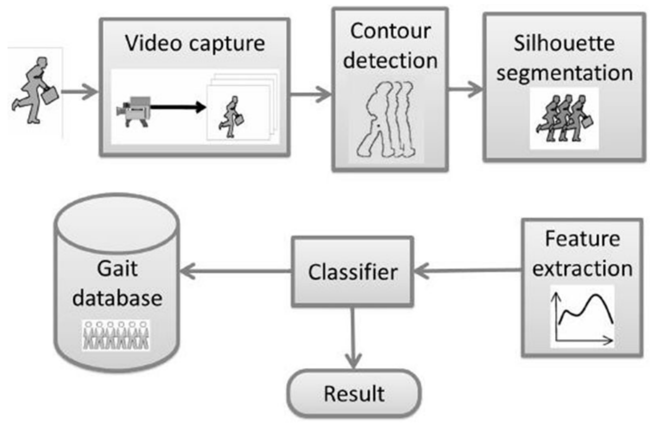

Fig. 1.1: Processes in Gait Recognition System

As shown in Fig 1.1, Data acquired by the gait data capture sub-system is further taken through different stages which are discussed later. Gait recognition algorithm used in the system processes this data (e.g. motion's video feed or sensor data) to contour detection, silhouette segmentation and feature extraction. Algorithms used during features extraction stage can be crucial as it is where one gait pattern is distinguished from another. Raw data requirements of a gait recognition algorithm depend on the system type. For example, some algorithms may be designed to process only video feed, while others may require video feed as well as sensor data.

Machine learning is increasingly marking its presence in many computers-based systems. Machine learning systems can improve themselves overtime by learning from data generated, captured and patterns. Gait recognition algorithms may have to deal with a lot of variations and their efficiency may be affected every time when there are unpredictable variations in raw data. Inclusion of machine learning in gait recognition algorithms can be the solution these system needs. They can learn and improve themselves every time they process a new sample of gait data.

Since no algorithmic approach can be absolute and there is always a scope for improvements, new capture methods and algorithms are always experimented upon to curb the inadequacies associated with the current gait recognition systems.

CHAPTER 2

LITERATURE SURVEY

The preliminary study for our project begins with first understanding the basic domain of the project, which is Biometric Authentication. For this, we looked into a survey on biometric authentication, and how various methods of biometric authentication help in contributing towards the security and privacy of a user by allowing them to be uniquely identified by unique parts of their own biology, which can be incredibly difficult to fake or break through [2].

We then delved deeper into this field by looking into a comprehensive study for biometric authentication systems. The sole purpose of looking into this paper in particular was to glean knowledge regarding the current trending systems that are in place for various methods of biometric authentication, as well as to clearly understand the challenges each of them pose. We also were able to learn more about the future trends in this domain, and gained an understanding of core concepts that we can apply to our own project [3].

The next step was to look into how Machine Learning plays a part within Biometric Authentication in particular, and to understand the various algorithms that can be used within this domain in order to enhance the success of such authentication systems. We also learned about the benefits of behavioural-based biometric user authentication, and could now understand how gait recognition is one of the basic types in this category of biometric authentication [4].

With these fundamental concepts in place, we then began to look into Gait Recognition in particular, starting off with the various ways in which a user's gait can be obtained as well as represented, as the dataset format plays a key role in how the project should be framed in terms of the input it is to take in. After a careful survey of this paper, we could conclude that the most effective representation of a person's gait was a Gait Energy Image (GEI) [5].

Looking further into gait representation, we also surveyed a paper that elaborated about GaitSet, and how a gait is regarded as a set for cross-view gait recognition. This information was purposeful as we could assess the angle of the silhouettes that would be required for a person's GEI dataset in order to accurately identify them [6].

Having now established the prerequisites that are needed for the project, we now look into the various types of models and Machine Learning methods that have so far been used for a Gait Recognition System. Firstly, we looked into the options available for a model-based gait recognition method, which elaborated on the various body poses and the necessity of human prior knowledge and how these things play a key role for such a system [7].

At this point in the survey, we soon learned the importance of Feature Representation and Extraction, as there are several instances where unknown covariates such as coats, bags, hats, etc., can reduce the accuracy of gait recognition method of biometric authentication. In order to understand and resolve this issue, we first looked into the various feature representation methods that are available in order to mitigate this problem [8] .

We, also understood the comparison of performances of different feature extraction methods in different scenarios of known and unknown covariate conditions, in particular, methods such as HOG, Haralick-Fisher representation methods perform in combination with well-known machine learning concepts such as SVM, Random Forest, MLP, etc. Through this paper, we recognized a disadvantage to these methods, in that the datasets need to be too large in order to ensure a proper success rate for various scenarios and several countless unknown covariate conditions, which is realistically not possible [1].

Hence, to resolve this final issue, we proposed to look into the possibility of using a one-shot learning algorithm, and looked into how image deformation works with the usage of one-shot learning, and how we can apply it to a gait recognition system in order to further enhance the results [9].

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CHAPTER 3

SYSTEM ANALYSIS AND DESIGN

3.1 HARDWARE AND SOFTWARE REQUIREMENTS

3.1.1 Hardware Requirements

Processor	:	32/64 Bit
Speed	:	2.0 GHZ (Minimum)
Primary Memory	:	4 GB RAM (Minimum)
Hard Disk	:	1 GB (Minimum)

3.1.2 Software Requirements

Languages Used	:	Python 3.7.0
Platform	:	Windows 7 or greater
Tools Used	:	Git, Visual Studio Code

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3.2 SYSTEM DESIGN

3.2.1 Existing System

Existing techniques employed for gait analysis are divided into model-based and appearance-based methods. The former requires high-resolution videos whereas the latter can deal with low-resolution imagery. Model-based approaches use the parameters of the body, appearance-based approaches on the other hand employ the features extracted directly from image sequences of gait. The simplicity of appearance-based methods and their robustness against noise make them more suitable for real-world scenarios. Appearance-based methods rely on silhouettes extracted from a gait sequence. Silhouettes contain important information about the stance and shape of the human body. Some of the existing techniques used for Gait Recognition include:

Random Forest

Random Forest, like its name implies, consists of a large number of individual decision trees that operate as an ensemble. As seen in Fig. 3.1, Each individual tree in the random forest spits out a class prediction and the class with the most votes becomes our model's prediction.

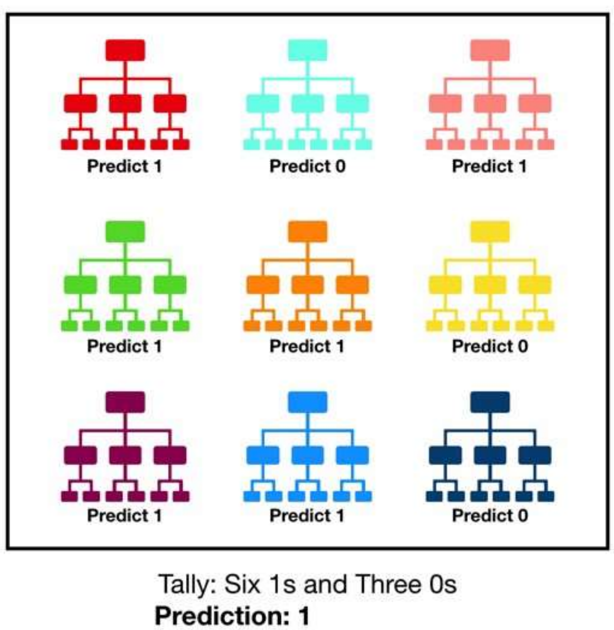

Fig 3.1: Random Forest

The fundamental concept behind random forest is a simple but powerful one, the wisdom of crowds. In data science speak, The reason that the random forest model works so well is: “A large number of relatively uncorrelated models (trees) operating as a committee will outperform any of the individual constituent models.”

The low correlation between models is the key. Just like how investments with low correlations (like stocks and bonds) come together to form a portfolio that is greater than the sum of its parts, uncorrelated models can produce ensemble predictions that are more accurate than any of the individual predictions. The reason for this wonderful effect is that the trees protect each other from their individual errors (as long as they don’t constantly all err in the same direction). While some trees may be wrong, many other trees will be right, so as a group the trees are able to move in the correct direction.

The Random Forest performs best in terms of classifying a GEI (Gait Energy Image) with an accuracy of 99.9%.

Disadvantages

1. Requires huge amounts of data to produce a proper forest.
2. It requires much computational power as well as resources as it builds numerous trees to combine their outputs.

Support Vector Machines (SVM)

The objective of the support vector machine algorithm is to find a hyperplane in an N-dimensional space(N - the number of features) that distinctly classifies the data points. To separate the two classes of data points, there are many possible hyperplanes that could be chosen. Our objective is to find a plane that has the maximum margin, i.e the maximum distance between data points of both classes. Maximizing the margin distance provides some reinforcement so that future data points can be classified with more confidence.

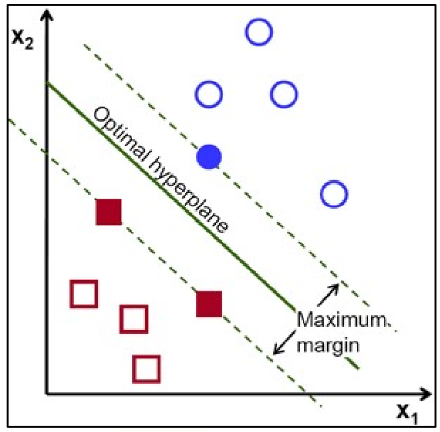

Fig 3.2 Possible Hyperplanes for Support Vector Machine

The above Fig 3.2 shows our objective to find maximum margin that can effectively classify the different classes. If the number of input features is 2, then the hyperplane is just a line. If the number of input features is 3, then the hyperplane becomes a two-dimensional plane and so on.

Disadvantages

1. Long training time on large data sets
2. Selecting the right kernel is not an easy task.
3. Sensitive to noise.

Multi-Layer Perceptron (MLP)

Multi-Layer Perceptron is a neural network where the mapping between inputs and output is non-linear. A Multilayer Perceptron has input and output layers, and one or more hidden layers with many neurons stacked together. And while in the Perceptron the neuron must have an activation function that imposes a threshold, like ReLU or sigmoid, neurons in a Multilayer Perceptron can use any arbitrary activation function.

The power of neural networks comes from their ability to learn the representation in your training data and how to best relate it to the output variable that you want to predict. In this sense neural networks learn a mapping. Mathematically, they are capable of learning any mapping function and have been proven to be a universal approximation algorithm.

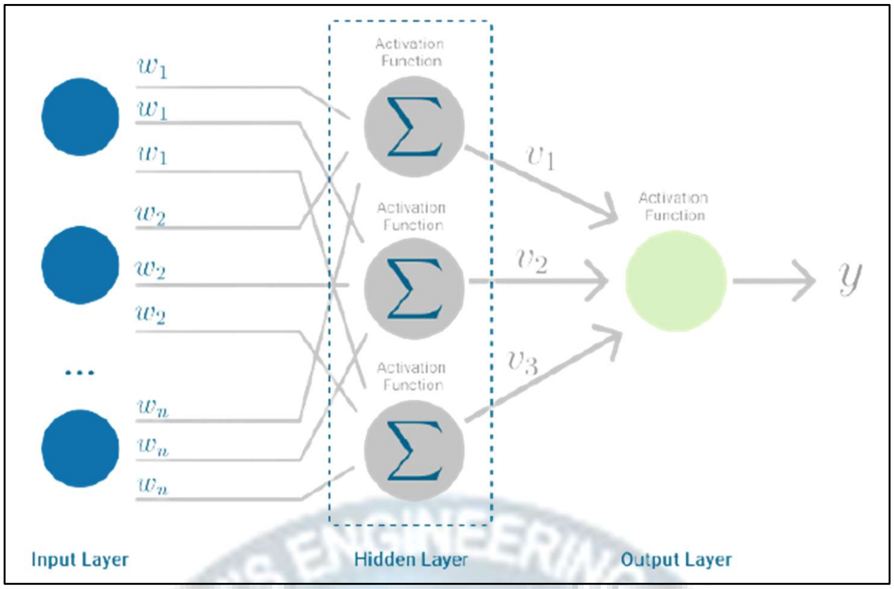

Fig 3.3 Multi-Layer Perceptron

As seen in the Fig 3.3, A Multilayer Perceptron falls under the category of feedforward algorithms, because inputs are combined with the initial weights in a weighted sum and subjected to the activation function, just like in the Perceptron. But the difference is that each linear combination is propagated to the next layer. Each layer is feeding the next one with the result of their computation, their internal representation of the data. This goes all the way through the hidden layers to the output layer.

Disadvantages

1. The proper functioning of the model depends on the Quality of training
2. Training time is long on large datasets

3.2.2 Proposed System

To overcome the disadvantages of the above existing systems, we propose on using One Shot Learning Algorithm. As the name suggests, we try and recognize a person in a single shot, .i.e. using a single image, which in our case is the Gait Energy Image (GEI) of a person.

Since we cannot train Models to recognize GEI every time a new GEI is added to the database, we try a different approach where we learn a similarity function. In particular, we want a neural network to learn a function d which inputs two images and outputs a degree of difference between them. So, if the images are similar, we want this output to be small and if it is different, we want it to be larger.

So mathematically, if d(img1,img2) $\leq \tau$ where τ is a threshold which is a hyper parameter, then we can predict that the two GEI are of the same person. If d(img1,img2) $> \tau$ then we can predict that the two GEI are of different person. Learning this function d allows us to address one shot learning problem. A good way to implement this function is to use a **Siamese Network**.

As shown in the Fig 3.4, we are used to input image $x^{(1)}$, which through a sequence of Convolutional Fully Connected Layers produce a Feature Vector.

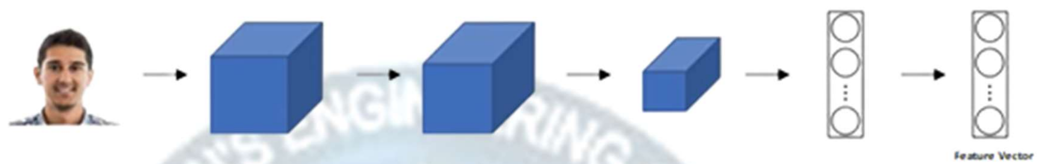

Fig 3.4: Generating a Feature Vector

Assuming the network produces a Feature Vector of size 128. We will call this $f(x^{(1)})$ which would be like an encoding for $x^{(1)}$. So now if you want to use the function d, We feed the second picture to the same Neural Network with same parameters and get a different feature vector of 128 length which would be $f(x^{(2)})$ representing encoding for image $x^{(2)}$. Now we need to learn Parameters so that if for any two images $x^{(i)}$ and $x^{(j)}$,

$$\| f(x^{(i)}) - f(x^{(j)}) \|^2 \text{ is small for similar GEI}$$

$$\| f(x^{(j)}) - f(x^{(j)}) \|^2 \text{ is large for different GEI}$$

Essentially, we find an image which outputs minimum difference and classify it as the image most similar to the testing image. Using the One-Shot Learning Algorithm, the testing data required is only a single GEI of a person and does not require any prior training.

3.3 PROJECT PLANNING

Project planning is the main part of project which decides whether the project will be successful or not. In the initial days, we learnt ways to implement One Shot Learning by using various libraries in Python such as numpy, tensorflow, sklearn, keras etc. Understanding these libraries served as a basis for our project.

Despite it's face-level complexity in architecture, the clean split up of the different modules made the planning and preparation in the later stages easier. We assigned various modules to different members of the team, and began collecting additional information more specifically for the implementation of each domain.

What is One Shot Learning?

One-shot learning is an object categorization problem, found mostly in computer vision. Whereas most machine learning based object categorization algorithms require training on hundreds or thousands of samples/images and very large datasets, one-shot learning aims to learn information about object categories from one, or only a few, training samples/images.

What is Siamese Network?

A Siamese network is a class of neural networks that contains one or more identical networks. We feed a pair of inputs to these networks. Each network computes the features of one input. And, then the similarity of features is computed using their difference or the dot product. Remember, both networks have same the parameters and weights. If not, then they are not Siamese.

By doing this, we have converted the classification problem to a similarity problem. We are training the network to minimize the distance between samples of the same class and increasing the inter-class distance. There are multiple kinds of similarity functions through which the Siamese network can be trained like Contrastive loss, triplet loss, and circle loss.

What is Triplet Loss?

Here, the model takes three inputs- anchor, positive, and negative. The anchor is a reference input. Positive input belongs to the same class as anchor input. Negative input belongs to a random class other than the anchor class. The idea behind the Triplet Loss function is that we minimize the distance between the anchor and the positive sample and simultaneously also maximize the distance between the anchor and the negative sample.

CHAPTER 4

MODULES

4.1 GENERATE GEI

The gait energy image is used to reflect the gait sequence of a cycle in a simple energy image using the weighted average method. The gait sequences in a gait cycle are processed to align the binary silhouette. If the gait cycle image sequence is B(x,y,t) gait energy image can be calculated by the following formula:

$$G(x,y) = \frac{1}{N} \sum_{t=1}^{N} (B(x,y,t))$$

where B(x,y,t) is the gait cycle image sequence, N is the number of frames in a gait sequence of a cycle, and t is the number of gait frames. Fig 4.1 shows the gait images of a cycle and Fig 4.2 shows the corresponding GEI.

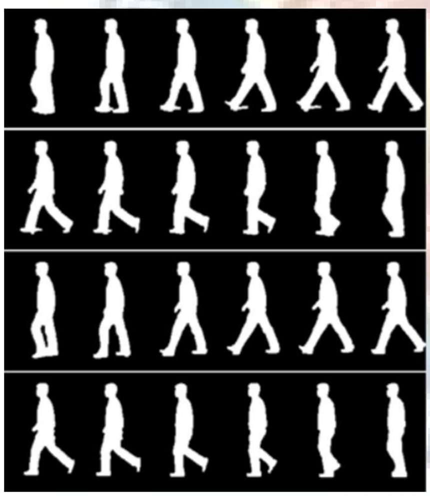

Fig 4.1: Gait Images of a cycle

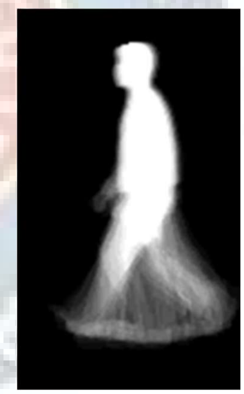

Fig 4.2: Gait energy image (GEI)

The color or luminance of the pixels in the figure can indicate the size of the body's parts when the person is walking. The white pixel points represent the parts which move slightly, such as head and trunk. Gray pixel points represent the parts which move significantly, such as the legs and arms. So, the gait energy image retains the static and dynamic characteristics of human walking, and it greatly reduces the amount of computation in the image processing.

4.2 EXTRACTING HOG AND LBP FEATURES

4.2.1 Histogram Oriented Gradients (HOG)

HOG, or Histogram of Oriented Gradients, is a feature descriptor that is often used to extract features from image data. It is widely used in computer vision tasks for object detection.

How is HOG different?

1. The HOG descriptor focuses on the structure or the shape of an object. HOG is able to provide the edge direction as well. This is done by extracting the gradient and orientation (or you can say magnitude and direction) of the edges.
2. Additionally, these orientations are calculated in 'localized' portions. This means that the complete image is broken down into smaller regions and for each region, the gradients and orientation are calculated.
3. Finally, the HOG would generate a Histogram for each of these regions separately. The histograms are created using the gradients and orientations of the pixel values, hence the name 'Histogram of Oriented Gradients'

4.2.2 Local Binary Pattern (LBP)

Local Binary Pattern (LBP) is a simple yet very efficient texture operator which labels the pixels of an image by thresholding the neighborhood of each pixel and considers the result as a binary number. Due to its discriminative power and computational simplicity, LBP texture operator has become a popular approach in various applications. It can be seen as a unifying approach to the traditionally divergent statistical and structural models of texture analysis.

The first step in constructing the LBP texture descriptor is to convert the image to grayscale. For each pixel in the grayscale image, we select a neighborhood of size r surrounding the center pixel. A LBP value is then calculated for this center pixel and stored in the output 2D array with the same width and height as the input image.

The main idea behind LBP is to describe the neighborhood of image elements using binary codes. This method is usually used to study their local properties and identify the characteristics of individual parts of the image.

4.3 ONE SHOT LEARNING

In the one shot learning problem, you have to learn from just one example to recognize the gait again. And you need this for most gait recognition systems because you might have only one picture of each of a person’s gait database. So one approach you could try is to input the GEI of the person, feed it too a ConvNet. And have it output a label, y, using a softmax unit with four outputs or maybe five outputs corresponding to each of these four person’s GEI or none of the above.

So that would be 5 outputs in the softmax. But this really doesn't work well. Because if you have such a small training set it is really not enough to train a robust neural network for this task. And also what if a new person joins your team? So now you have 5 persons you need to recognize, so there should now be six outputs. Do you have to retrain the ConvNet every time? That just doesn't seem like a good approach.

So instead, to make this work, what you're going to do instead is learn a similarity function. In particular, you want a neural network to learn a function which going to denote d, which inputs two images and outputs the degree of difference between the two images. We use various things like a Siamese Network, Triplet Loss, Convolutional Neural Network for Feature Vector extraction to implement One Shot Learning Algorithm.

4.4 MULTI-LAYER PERCEPTRON

Our project uses Multi-Layer Perceptron as one of the comparison methods. Multi layer perceptron (MLP) is a supplement of feed forward neural network. It consists of three types of layers—the input layer, output layer and hidden layer. The input layer receives the input signal to be processed. The required task such as prediction and classification is performed by the output layer. An arbitrary number of hidden layers that are placed in between the input and output layer are the true computational engine of the MLP.

Similar to a feed forward network in a MLP the data flows in the forward direction from input to output layer. The neurons in the MLP are trained with the back propagation learning algorithm. MLPs are designed to approximate any continuous function and can solve problems which are not linearly separable. The major use cases of MLP are pattern classification, recognition, prediction and approximation.

4.5 RANDOM FOREST

A random forest is a supervised machine learning algorithm that is constructed from decision tree algorithms. This algorithm is applied in various industries such as banking and e-commerce to predict behavior and outcomes.

A random forest is a machine learning technique that's used to solve regression and classification problems. It utilizes ensemble learning, which is a technique that combines many classifiers to provide solutions to complex problems.

A random forest algorithm consists of many decision trees. The 'forest' generated by the random forest algorithm is trained through bagging or bootstrap aggregating. Bagging is an ensemble meta-algorithm that improves the accuracy of machine learning algorithms.

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