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A SURVEY ON GAIT ANALYSIS AS A BIOMETRIC SYSTEM

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Abstract- Psychological studies indicate that people have a small but statistically significant ability to recognize the gaits of the people they know. A gait signature will be obtained using the spatial and temporal features obtained by a pipeline of a computer vision and deep learning models. The signature is a vector which can be compared to the existing stored vector which can authenticate a person.
Keywords- Deep Learning, Gait, Artificial Intelligence, Biometrics, Security

1. INTRODUCTION

Biometric is the term for body quantifications and calculations, refers to human characteristics. Subsisting biometrics include face, dactylogram, iris, hand, voice, etc. Human gait refers to locomotion achieved through the kineticism of human limbs. Gait is currently utilized by medicos to treat patients with diminished motor faculties. All the current biometric authentication systems are evasive in-nature. Psychologists suggest each person can be distinguished by utilizing their gait sequence. We aim to identify those subtle features to create gait signatures.

To identify a person using gait as a biometric, the system utilizes computer vision in real time. The system will learn to recognize humans from the video frames and capture the temporal information of the person to recognize the gait pattern of the person. A gait signature will be obtained utilizing spatial and temporal features utilizing deep learning methods like neural network to obtain the output as a vector which can then be used to identify if any registered person is in the frame or not. This enables hassle free sanction without having the desideratum to interact with any external hardware such as dactylogram scanners, iris scanners, etc.

Human Gait as a biometric is not an extensively researched topic. Non - invasive biometric authentication methods are not put to utilize even with so many technological advances. Human gait has a wide variety of use cases such as security, medical utilization, bulwark, etc. Gait be acclimated to identify patterns in other entities by utilizing the same architecture.

Gait cycle: Steps start with initial contact of one foot and ends with initial contact of other foot. Stride starts with the initial contact of one foot and ends with the next initial contact of that same foot, so it is made out of two steps.

1.1 Gait cycle is divided into 2 phases-

Stance: In this phase, right leg has to complete different tasks with heel strike, the leg has to accept the weight of the body. This is loading response which gives 10% of gait cycle. Loading response ends once contralateral foot lifts off the ground. After loading response until the point heel is off the ground is called mid stance which gives 30% of gait cycle. The heel of the right foot starts to lift while contralateral leg has initial contact with ground is terminal stance which gives 50% of gait cycle. Contralateral leg is preceding to make full contact with the ground, right leg lifts off further from ground this is called pre-swing which gives 60% of gait cycle. [13]

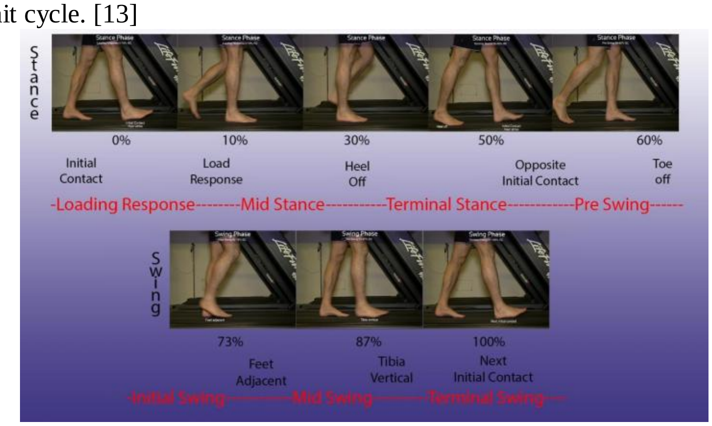

Fig. 1.1 Gait cycle representation [13]

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Swing: Swing phase is divided into three parts- Initial swing starts from toe off until feet are adjacent which gives 73% of gait cycle. Mid swing lasts until the tibia is vertical and gives 83% of gait cycle. Terminal swing is when the heel strike of right leg and gives 100% gait cycle. [13]

2. LITERATURE SURVEY

F.M. Castro, M.J. Martinez-Jiménez, N. Guil, N. Pérez de la Blanca proposed paper proves to be the base paper for further research as it presents a solution to find signature of people utilizing just a single CNN to process multiple color images to identify the signature of an ambulating person. This method enables us to work with low resolution images. The CNN is utilized to extract features in each frame and engender a signature of a person. [1]

M.D. Jan Nordin and Ali Saadoon. presents implementation of biometric gait recognition approach utilizing modeling by human skeleton over the second approach modeling by human body contour. Human body contour cannot detect kineticism details and deal with self-occlusion. Skeleton method is hard to get but can describe kineticism joints. To build skeleton model some paramount points in the silhouette are culled which can engender the features representing a person's gait. Using skeleton model shows its precision in kineticism details and kineticism joints [2].

Martin Hofmann, Shamik Sural and Gerhard Rigoll in their paper addresses the problem of occlusion by presenting new database. This database also addresses three new kinds of variations which have not yet been addressed by other datasets. More specifically these variations include hands in pocket, wearing a backpack and wearing a gown. GEI Gait Energy Image is used to extract the Gait features which is compared with colored Histogram Method and cropped GEI variant. goal is to recognize a person, which has only been seen once before and classify using nearest neighbor.[3]

Wei Lu, Wei Zong, Weiwei Xing utilized joint distribution of kineticism angles and data in time domain is utilized to build histograms for gait apperception. 2D video database and 3D kineticism capture database is utilized to find distribution spectrums. The distance vectors are acclimated to find homogeneous features. Predicated on kindred attribute between histogram, classifier is utilized for apperception.[4]

Israel Raul TiñiniAlvarez And Guillermo Sahonero-Alvarez proposed a better way of apperception by utilizing a modified gait representation of gait sequence. The proposed method achieves dimensionality reduction by applying principal component analysis and relegation employing linear discriminant analysis. The model was tested utilizing the CASIA-B benchmarked database and the performance of the model was quantified utilizing the rate of correct relegated examples. To address issues like transmutation in appearance, they have proposed to utilize a feature representation that takes both dynamic and static regions of silhouettes. This way, more robustness against covariates and better discriminative performance are expected.[5]

Mohan Kumar H P Nagendraswamy H S covers the survey of capturing the energy variations in static and dynamic part in gait sequence. Change energy images (CEI) are engendered utilizing sequence of silhouettes of gait cycle. Radon transform is applied to this sequence and the values are obtained for four different angles. The homogeneous attribute is then calculated utilizing probe sequence and reference gait sequence.[6]

Zifeng Wu, Yongzhen Huang, Liang Wang, Xiaogang Wang and Tieniu Tan, Fellow, proposed a paper to record and identify gaits of people analyzed at various angles of view-points. The silhouettes are taken into consideration using deep CNNs and is used to perform similarity learning to re-identify the person at a later stage. By using different view angles, a 3D structure of the person in perspective can be constructed which provides much more efficiency than a regular image.[7]

Darko S. Matovski, Mark S. Nixon, Sasan Mahmood and John N. Carter developed robust and precise gait recognition algorithms by considering five covariates that affect apperception: viewing angle, shoe type, ambulating surface, carrying objects and elapsed time between sequences being compared. Understanding the effect of a particular covariate on the apperception performance is crucial and depends on the algorithm adopted. This paper implements subsisting model-free approaches to examine the effect of time and other covariate factors. It utilizes Gait Energy Image (GEI) since it is one of the most popular gait representations used and additionally Gait Entropy Image (GEnI) as it is a recent method and it is believed to be invariant to transmutations in covariate factors. [8]

3. PROPOSED ARCHITECTURE

The proposed system includes a pipeline to identify a person and at the same time identify the pose by using marking the various structural points in a body including and not limited to hands, elbows, shoulders and other joints and peculiar parts. A pre trained Convolutional Neural Network identifies a person and outputs a vector representing the positions of the individual body parts which can be then mapped to the input image to visualize the pose.

These features are then used to identify the temporal feature by using a Recurrent Neural Network to identify the relation between one vector and its successive vector. By using this approach, we aim to correlate the vectors with each other. The Long Short-Term Memory Network makes use of gates to store information over longer periods to retain information even after processing 40 frames of images. The RNN processes every vector and outputs a single vector which would act as a signature for a particular person. This signature is stored in the database and then can be further used to re-identify a person by comparing the similarity between the vectors. Triplet loss can be used to compute the similarities between the vectors to differentiate various signatures effectively. The RNN encodes the multiple vector inputs into a resulting equidimensional vector.

To implement this system in real life, we setup a pair of the above system at two distinct locations: one of them being an entrance from when the gait can be identified and stored and the other at a different location where the re-identification would take place i.e. authorizing a person to access a certain location. The setup includes a single lens RGB camera which supports a frame rate of 24fps. The camera would be connected to a remote server which would aid in processing the live video feed by capturing it for 3-5 seconds. This leaves room for processing multiple people if applicable. This system is not a complete replacement for the current invasive methods for authentication because of technical limitations. Due to its predictive nature it does not guarantee an absolute decision of verifying a person effectively. In fact, this system can be used to identify a person with high authority.

3.1 System Architecture

The proposed system architecture is posited here and the various elements in this system are described in this section.

The video input is converted into frames of individual images for the system to process. The image could be processed using threshold filters to retain only the necessary parts of the body so that the neural network is forced to use the body structure to learn the signature.

This pose at every instance is collected as a vector, each representing the pose at a specific time. The vectors can be collected for a period of 3 seconds of video input which approximately converts to 72 frames of which 40% of the frames would be blurred out because of the motion involved while walking. So, using the remaining 42 frames, we get the individual pose vectors, thus obtaining the spatial features.

CNN: The Convolutional Neural Network used would be a pre-trained model as mentioned earlier. Many neural networks have been implemented to identify body parts and estimate human pose. A batch of single images would be processed by the CNN, producing a 1-dimensional vector constituting the pose of the person at a certain instance of time. The vectors collected from all the subsequent frames would be then packed into a matrix form to proceed through the pipeline.

Vector Matrix: The vector matrix is a n*m dimensional matrix in which n is the number of features from the CNN and m is the number of frames in the video feed.

LSTM: Long Short-Term Memory network consists of gates which are used to process time-based data and can be used to correlate information change from an image to its previous image frame. LSTM consists of gates which is useful in this scenario where the number of vectors would be large and the tendency to forget the information is higher. So, by using a LSTM network, information according to its importance is retained and would help in creating the final gait signature.

GAIT Signature: Effectively, the pith of this system is the vector of numbers which would act as a signature unique to a particular person. This vector is stored in the database and is meant to be compared to a new signature to check the distance between the two vectors to predict whether the new signature belongs to a person already registered or not.

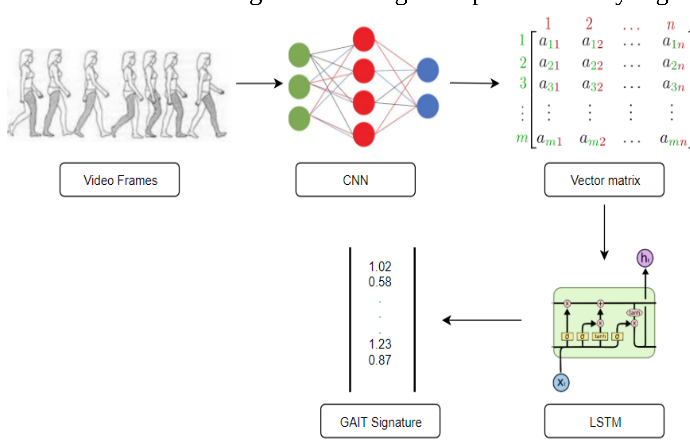

Fig 3.1.1 Proposed architecture [9][10][11][12]

3.2 Requirement Analysis

The requirements associated with this system are discussed which includes the software and hardware prerequisites.

3.2.1 Software

The system records the video feed and stores it temporarily for processing. Once the signature is obtained, the video can be erased. A central server with python and other dependencies installed are the only requirements. The system is proposed to run on any operating system and all the dependencies are open source projects.

3.2.2 Hardware

The hardware requirements needed for this system to compute the signature smoothly is rather common. It includes an RGB camera or a surveillance camera which might be already in use. The server must have a minimum of 16 GB of RAM and a

DDR5 graphics card. The bandwidth on the wireless transceiver must be good enough to support almost real-time transfer of video stream or a wired transmission system can be incorporated to minimize data loss.

4. CONCLUSION

The Gait biometric system will learn to recognize humans from the video frames and capture the gait features of the person to recognize the gait pattern of that person. A gait signature is obtained by using a neural network which is a deep learning method. Spatial and temporal features are used in neural network to obtain the output as a vector which can then be used to identify if any registered person is in the frame or not. This biometric system will help us to enable hassle free authorization without having the need to interact with any external hardware such as fingerprint scanners, iris scanners, etc.

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