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Research Article

Gait Recognition Based on Deep Learning Using Accelerometer and Gyroscope in Smartphones

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ABSTRACT

Gait Recognition is difficult when compared to other biometrics and has an unobtrusive advantage, but it has little interaction among the users. The gait dynamics are captured using accelerometer and gyroscope, which are the initial sensor used in the smartphones. The gait data is inexpensive and convenient to collect using the inertial sensor integrated in the smartphones which an average person can commonly use. The gait recognition utilizing the smartphones in the wild is proposed in this paper. The traditional method for gait recognition requires a person walking on a specified road, walking speed etc. The inertial data is collected for gait recognition under a free situation without knowing the knowledge of data collection in a user walk. The deep learning techniques are utilized to obtain authentication performance and person identification to learn the gait based on a biometric model based on the person walking data. The robust gait feature representation is obtained using the proposed hybrid deep learning technique. The space and time domain is successively abstracted by the convolution neural network.

Key Words: Gait Recognition, Accelerometer, Gyroscope, Convolution Neural Network

I. INTRODUCTION

Every year the measure of sensitive information that can be gotten through smartphones surge. This lifts the needs including recognition frameworks that secure the admittance to this data. Conventional access control frameworks, for example, PIN numbers or examples have been end up being monotonous to the users and requires him/her to recall either the pattern or PIN, received at the point wherein the client just eliminates the entrance control framework. Biometrics proposes a more regular methodology, in view of something users are (El-Basioni, El-Kader, and Abdelmonim 2013). Execution of biometric frameworks into mobile phones has come about very

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effective in their sending and utilization, as agreeable and usable interfaces have been accomplished for controlling the admittance to the mobile phones.

Biometric frameworks, such as fingerprint have effectively been actualized as access control frameworks for smartphones (Handa, Singh, and Saraswat 2019). The user acknowledgment appears to be high for its service. Since fingerprint sensor require very little connection and the user considers it to be an agreeable method of accessing telephone. By the by, different modalities, for example, walk acknowledgment dominates in this effectiveness of utilization since it doesn't need direct collaboration with the users.

Independent investigations in medication and brain research perceive that every individual possesses a particular strolling style that permits his acknowledgment. The distinguishing proof of that gait pattern has pulled in much investigation. Although, the first investigation were directed in laboratories equipped with dedicated facilities, the latest thing is to utilize compact sensors, specifically 3-axis accelerometers (Lee et al. 2007), for dissecting the human walk. Adjusting to the worldview of universal processing, several state-of-art investigates propose to misuse the accelerometer implanted in most of the smartphones accessible available (Nishiguchi et al. 2012). In fact, smartphones regularly incorporate an accelerometer, to adjust the display when the direction of the smartphone changes or for videogames.

Traditionally, gait based validation has been concentrated through analyzing the recordings of human movement (Oh, Choi, and Mun 2013). However, the universality of advanced smartphones outfitted with accelerometers and gyroscope has opened another measurement to gait based confirmation in-spite of the extraordinary capacity to catch gait designs by accelerometer and gyroscope. In addition, wide spread applications and advances in AI have brought about improved exactness. This review is an endeavor to bring a comprehensive, generally modern research and investigation of advances and the condition of training in gait based validation.

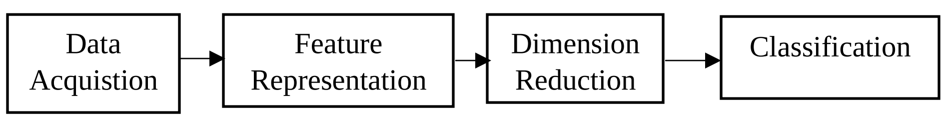


Figure 1: Overview of Gait Recognition

Inconspicuousness is particularly significant for a biometric framework that should work in a discrete method. Among different biometrics, gait fulfills the prerequisite of being unobtrusive and challenging to conceal (Minaee et al. 2019).
Gait biometric includes recognizing an individual dependent on his/her walking features. Mostly, gait response can be performed on two types of information: a succession of pictures (e.g., from a video), or an inertial step time arrangement created by inertial sensors. In the event that walk pictures or inertial stride time arrangement can be caught, we can perform step acknowledgment and consequently individual recognizable proof.
Nowadays, with appearance of universal gadgets, including sensors, smart gadgets (telephones, tablets) with little and wearable single-board figuring frameworks, unavoidable registering has gotten basic in this specific circumstance. Perhaps the main parts of inescapable registering is interconnectivity and interoperability of omnipresent device. Such idea is otherwise called Internet

of Things (IoT) with primary reason for embedding intelligent device, advancements on a few levels, including information, correspondence, dynamic and application level (Gubbi et al. 2013). IoT goes inseparably with distributed computing, addressed as the calculation worldview of things to come. In this, availability is the main issue that should be settled. However, abilities of most recent universal gadgets, including their exhibition and self-sufficiency, guarantee effective information handling and correspondence with cloud framework that depends on the transmission capacity and cost of information move. Accordingly, such worldview is required to turn out to be totally practical since patterns show that proportion transfer speed cost is developing altogether. In such manner, one can profit by the accompanying: efficient enormous information stream transmission, large computational preparing on server side, sensible dormancy and huge information store. Thinking about these variables, inertial sensors as a critical piece of pervasive gadgets ought to reinforce their job as they can be applied for more unpredictable errands that are performed constantly. In this unique situation, the methodologies that consider progressed development and gait detection dependent on inertial information ought to be taken into cautious. This also incorporates gait recognition methods that could get perhaps the main techniques either in the field of biometry, security, telemedicine, biomedical designing and numerous others.

II. RELATED WORK

Gait using Inertial Sensor

Nowadays, the use of inertial sensors in performing gait analysis as an important group of wearable sensors (Tao et al. 2012) has become essential in several fields of research including neuro-rehabilitation, sport medicine, biomechanics, etc. (Muro-De-La-Herran, Garcia-Zapirain, and Mendez-Zorrilla 2014). Inertial sensors can quantify single or multi-point movement directions of single or numerous body fragments of the subject during walk.

During the estimation time frame, univariate multivariate signs are procured that give quick data on estimated amount (Li et al. 2020). Thus, gait pattern can be surveyed as far as gait pattern that can be deciphered in a few different ways to find or to notice explicit wonder, including between and intra-subject appraisal of gait varieties dependent on walk design similarity. Then again, considering the way that every individual has a one of a kind way of strolling, gait appraisal depending on inertial sensors can be in practically equivalent to route misused for the issue of gait based acknowledgment. Thus, gait can be deciphered as a biometric quality and, subsequently, inertial sensors can possibly assume a significant part in the field of biometry. Subsequently, the use of biometric technique (Meng et al. 2014) can essentially reinforce security angles which can be addressed using a few use-case situations, including a novel check method that can broaden or even supplant prevailing security components, burglary identification, profile exchanging, client following, backing to portable medical care frameworks, and numerous others.

Moreover, it ought to be referenced which provide improvement of inertial sensor-based gait recognition approaches arose all the while with the wide event of universal shrewd gadgets, particularly cell phones and tablets. These days, joining of inertial sensors in brilliant gadgets has gotten a norm. (Yang and Li 2012) two significant realities that uncover the relevance of inertial sensors as a significant piece of omnipresent gait device as far as gait analysis. In the first place, there is a huge pool of potential clients that have, convey and utilize strong gadgets consistently. Truth be told, it very well may be accepted that real quantity will overextend these assumptions. Second, inertial sensors as a piece of savvy gadgets is integral asset and are not, at this point carefully restricted to help basic and insignificant assignment just as it was principally planned at their appearance because of a few constraints that were part of the way or completely defeat as of late with the most recent accomplishments in the field of unavoidable figuring. Truth be told, it has effectively been shown that inertial information (Caldas et al. 2017) obtained by sensors in omnipresent savvy gadgets can be utilized to survey clients' movement in cutting edge way, including confinement as quite possibly the most charming difficulties as of late, just as action acknowledgment and progressed movement examination including stride. Such methodologies have been analyzed in a few zones, for the most part in sports and clinical applications (Yang and Li 2012). Thus, the hypothesis that gait recognition depend on inertial data developed by using omnipresent smart devices that has become practical and has addressed by several exploration groups recently.

Gait Recognition using Deep learning

Several deep neural networks is utilized to remove the signal features from the image systems and the inertial time series. Since the outstanding capability of CNN in image-characteristic perception, numerous researchers engaged CNNs for gait recognition (Wu et al. 2016). In (Wu et al. 2016), three deep CNNs are created for gait recognition, in which the user utilize gait descriptions as input. Feature maps are fused at various convolutional stages to enhance the accuracy of classification. In (Takemura et al. 2017), deep CNNs with triplet ranking loss and contrastive loss are suggested for cross-view gait recognition, and high presentations are obtained from person identification and authentication. In (Yuan and Zhang 2018), based on the extracted gait data by a periodogram-based gait separation algorithm, deep CNNs are erected for classification of gait.

(Wolf, Babaee, and Rigoll 2016) present method to wrestle these challenges in Gait Recognition adapting newly established concepts in deep learning. A 3D Convolutional Neural Network (CNN) is accessible using spatio-temporal data in which it is trying to predict a general descriptor for human gait invariant for view angles, color and different walking conditions.

Due to its powerful feature learning abilities, convolutional neural networks (CNNs) have attained great realization in object recognition task nowadays. Several CNN-based gait recognition methods (Wu et al. 2016)have been proposed which can automatically learn robust gait features from the given training samples. Additionally, using CNNs, feature extraction execution and perform recognition within a single framework using train samples. (Wu et al. 2016) performed cross-view gait recognition by developing three convolutional layer network using the subject's GEI as input.

In (Wolf, Babaee, and Rigoll 2016) used 3D convolutions for multi-view gait recognition by taking spatio-temporal characteristic from raw images and optical flow information. In (Yu et al. 2017), generative adversarial nets is utilized to design a feature extractor in order to acquire the invariant characteristic. In (Yu et al. 2017), they further enhance the GAN-based technique by accepting a multi-loss scheme to enhance the network to surge the inter-class distance and to diminish the intraclass distance at the same time.

III. GAIT DATA COLLECTION IN THE WILD

The gait data collected using smartphone is discussed in this section. The inertial sensors introduced in the smartphone and how the inertial sensor partition the walking and non-walking data using the described algorithm and then the segmentation of the gait cycle is elaborated in this section

A. Integrated Inertial Sensors in Smartphones

A typical inertial sensor such as accelerometer and gyroscope are embedded in the smartphones. Three directional axes X, Y and Z measure the inertial dynamics using accelerometer and gyroscope (Justa, Šmídl, and Hamáček 2020). Based on the principle of the acceleration, three axes accelerometer works to predict the smartphone acceleration in X, Y and Z direction. The change in 3D space in linear velocity of the smartphones is reflected by the acceleration in three direction. The angular velocity of the smartphone is captured using the three axis gyroscope embedded in the smartphone in which the pattern of the movement is described. Based on the movements of the user, the smartphone accelerate and rotate. The source of the gait dynamics collected is individually unique. For acceleration and gyroscope, hardware synchronization is provide itself by smartphones. The slight effect may occur in the synchronization when the android interface record inertial data.

B. Data Extraction for Gait

The knowledge in the collection of inertial data in the smartphone is not known. The gait data consist of walking and non-walking session. The gait identification is achieved using the feature extraction of the walking data. The inertial time sequence are uninterrupted in both time and space domain and the walking and non-walking data are consequently different. The DCNN algorithm is utilized in the time-series segmentation problem.

C. Segmentation of Gait Cycle

The performance of the gait with cycle-partition data is improved compared to the non-cycle partitioned data. The deep learning segmentation network extract the gait data. The accelerated data is used without the generality loss for portioning of data. The fluctuation of the gait data is cannot be stably reflect as the accelerator single axis in which smartphone can be randomly moved. The perfect acceleration beside three axis direction is abrupt to the ground values.

IV. GAIT RECOGNITION WITH DEEP NEURAL NETWORK

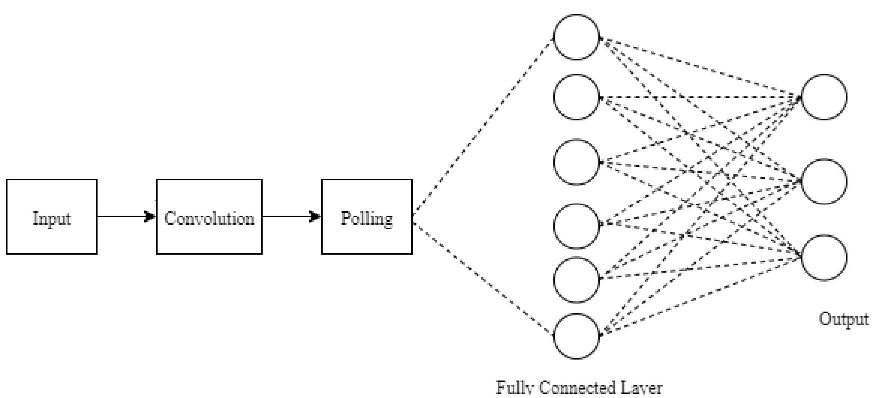


Figure 2: The network of Gait Identification

The gait identification involved in the gait recognition which identify a sample form the set of candidate in the dataset. The signal in X, Y and Z axis are related at same time series of the accelerometer. The gait data is partitioned into six axis based on the accelerometer and gyroscope. The deep learning Convolution Neural Network efficiently process the data (Taloba, Eisa, and Ismail 2018). The DCNN when combined with LSTM provide full utilization of strength and the temporal and spatial feature are learned to enhance the feature representation of the gait recognition system. The DCNN and LSTM is fused for performing the feature concatenation which is fully connected in the successive layer for the gait classification.

V. EXPERIMENTAL ANALYSIS

The inertial data collected from the smartphones contains six dataset which consist of data alignment, comparison method selection, training strategy etc. The evaluation for identification and authentication for gait in biometric identification is determined

Dataset

A large amount of samples are required for deep learning method which contains in whuGAIT dataset. The inertial data in dataset is collected based on the unconstrained condition in the free environment for recognition of gait. Dataset contains the data collected in daily life.

Dataset Name	Usage	Number of Subjects	Time-fixed or Interpolation	Overlap in sampling	Training Samples	Testing Sample	Alignment
Dataset 1	Classification	118	Interpolation	1 step	33,104	3,740	NA
Dataset 2	Classification	20	Interpolation	0	44,339	4,936	NA
Dataset 3	Classification	118	Time-fixed	1 step	26,283	2,991	NA
Dataset 4	Classification	20	Time-fixed	0	35,373	3,941	NA
Dataset 5	Authentication	118	Interpolation	1 step	66,542	7,600	Horizontal
Dataset 6	Authentication	20	Interpolation	1 step	66,542	7,600	Vertical

Figure 3: Information of whuGAIT dataset

The sample data contains 3-axis of gyroscope data and 3 axis of accelerated data. The sensor data utilize the sampling rate of about 50Hz.

The android APP is developed and installed in the smartphones in which the gyroscope and accelerator contains the sampling rate of 50Hz. The data collection process is started when the data when the user inputs the identified information. The data is collected in long period which contains walking and non-walking data. The APP captured the walking data for long time. There are seven dimension in the captured data such as time stamp, triaxial value of gyroscope and triaxial value of accelerator.

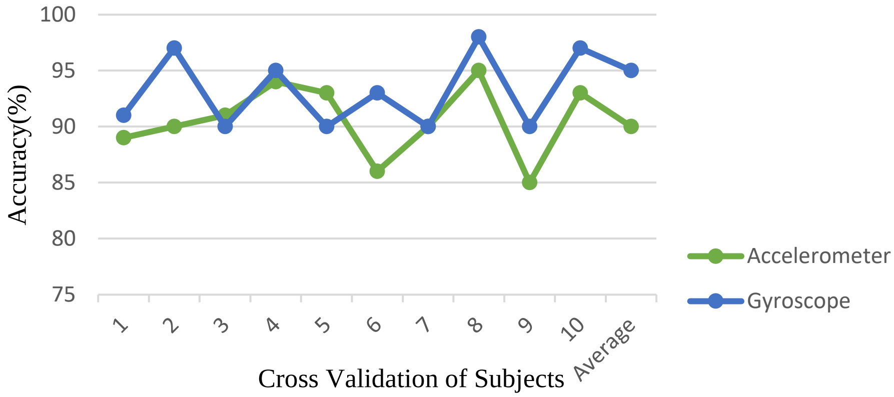
Dataset Name	Number of Subjects	Training Samples	Testing Sample
Dataset 7	10	519	58
Dataset 10	118	1022	332

Figure 4: Data used for training and testing

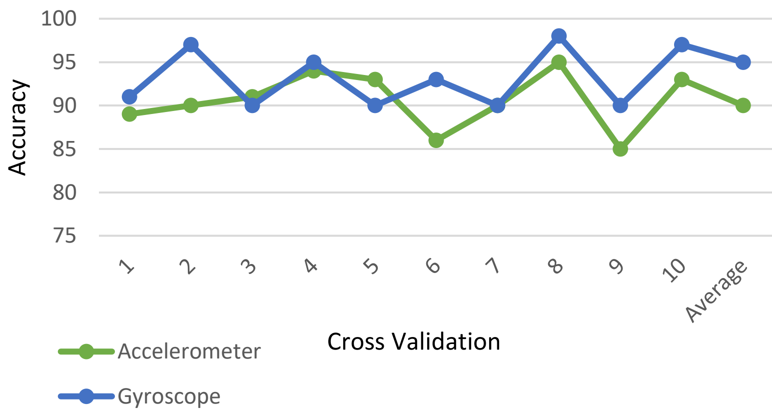
The dataset contains 118 subjects in which the feature extracted samples are utilized for training and testing. These samples provide better accuracy in the recognition of gait biometric in which the data collected form the inertial sensor are used for the extraction of the training and testing samples for gait recognition.

VI. RESULT AND DISCUSSION

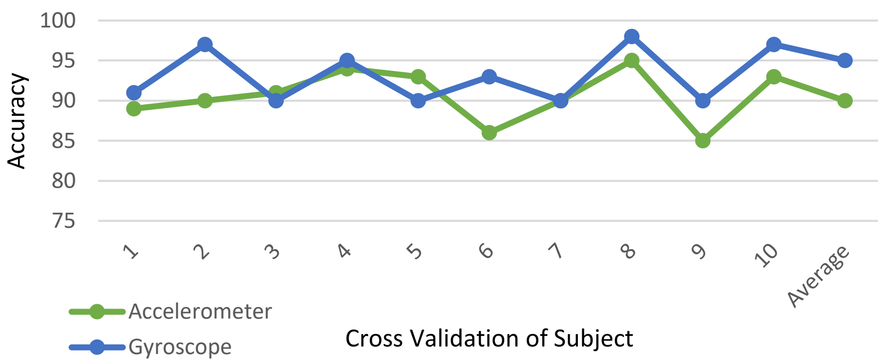
The accuracy is predicted based on the inertial sensor embedded in the smartphones of DCNN model in which 10 cross validation subject are utilized. The average accuracy measured for each subject in the dataset. The green and blue marks represent the accuracy based on the inertial sensor such as accelerometer and gyroscope.



a) Right Ankle



b) Right Wrist



c) Right Knee

Figure 5: Performance of Cross Validation of Inertial sensor

The accelerated data in subject provide high data accuracy in gait identification. It is observed that the dynamics of the gait is mostly captured using the movement of lower limb. The gait identification is obtained by predicting the movement of knee, wrist, ankle etc., which is collected using the sensors in smartphones. The incorporating the complementary discriminative information generated from different sensors can be improved.

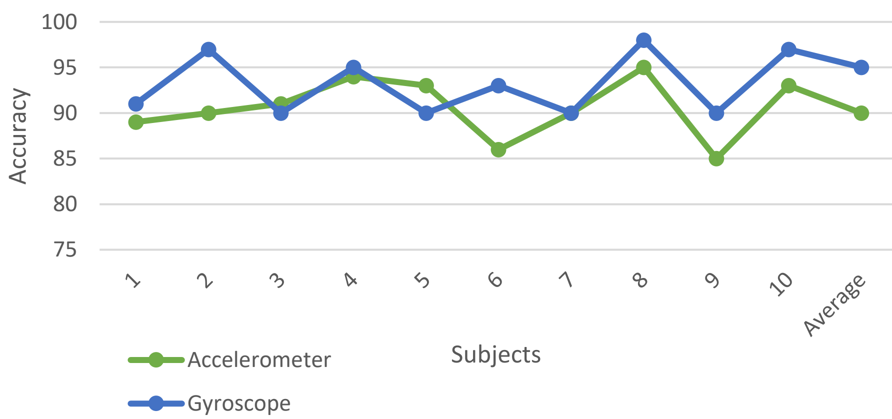


Figure 6: Performance Comparison of Gait Identification using DCNN

The figure 6. demonstrate enhanced accuracy prediction of gait identification using DCNN. The DCNN model adversely change the identification of gait for biometric function. The gait identification using DCNN by gathering the data from inertial sensor provide better accuracy performance.

VII. CONCLUSION

In this paper, gait recognition based on the deep learning using accelerometer and gyroscope in smartphones was analyzed. The DCNN is analyzed in inertial feature representation for gait recognition. The smartphones are utilized in any situation for data collection and how the data collected is fully known. The initial data is partitioned using recursive convolutional neural network and features are combined fused for efficient segmentation. The convolutional feature map is obtained from the time series by using the proposed convolution neural network. The LTSM is combined with DCNN because the convolutional time series property is remains with designed convolution kernels. The time series features is employed using LSTM for gait recognition. From the proposed system the performance of accelerometer data is better than gyroscope data and performance is improved using DCNN and LSTM for gait feature extraction. The vertically aligned inertial data provide better result for DCNN and LSTM than the horizontally aligned data.

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