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Remora Optimization Based Sample Weighted Random SVM For Human Gait Authentication

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ABSTRACT- In this paper, we present a novel ESVM-SWRF method for authenticating human using a gait cycle. The different covariates related to walking are analyzed and investigated. The walking speed of people may change due to the individual body structure, gender, and age thereby creating a complex situation. Based on the studies over past decades, different perspectives with cross-speed gait authentication were suggested. The factors influencing the identification of gait are some of the covariate factors namely walking speed, injuries, walking surface, viewpoint, and clothing. Our proposed work uses an effective dataset CASIA-C. Most of the existing techniques achieved a nearly 100% authentication accuracy rate for normal walking conditions but their performance is not optimal when applied under different covariate conditions. Our proposed work proves a high accuracy rate of 89% for different covariate conditions compared to other existing methods.

General Terms: Biometrics, Authentication.

Keywords: Support vector machine, sample weighted random forest, Gait, Remora optimization.

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1. INTRODUCTION

Nowadays the need for security of people is increasing and the people in monitoring system should be detected quickly. Biometric mode of detection has the facility to authenticate a person through their behavioral or physiological features [1]. Currently for the authentication purpose physiological features such as vein, iris and face are utilized though the behavioral properties will be investigated in the upcoming works. Human gait is considered as a biometric trait applied for detecting the person based on walking pattern. They play a vital role in video monitoring, forensic science and security applications [2]. The covariate factors like load carrying conditions, view angle, fatigue, drunkenness and clothing variation affects it by few limitations. These elements reduce the penetrating ability of gait. The gait has the facility to perform the function in a distance and equally execute the function in videos of low resolution. The gathered videos are obtained using vision-based sensor and the characteristics of gait are processed and analyzed for the purpose of authentication [3].

For surveillance applications, the person's innate characteristics still create it invaluable in which these factors reduce the discerning gait ability [4]. The most challenging factor is changing of speed among these factors. Speed variations in walking speed affect the stride length reduction [5]. Because, the changing of speed causes variations in the movement of various parts of human body namely ankles, knees, hip and arms. The walking speed of people changes due to the individual body structure, gender and age thereby creating complex situation [6]. Based on the research over past decade many different perspectives with the cross-speed gait authentication were suggested. The factors influencing the identification of gait are some of the covariate factors namely walking speed, injuries, walking surface, viewpoint, and clothing [7].

The models which are examined and checked under the predefined covariate status are termed as known covariates and the models which are investigated with normal walk under various factors of covariates are termed as unknown covariates [8]. However, the known covariates are efficient in performing the authentication mechanism. In the phase of training the majorities of the gait identification feature utilizes gait sequence in predetermined condition and in the phase of testing these sequences are handled over different covariant factors [9]. These issues are overcome by applying the technique named ensemble SVM and sample-weighted random forests (ESVM-SWRF) via Remora optimization [10].

The main contributions of this paper are presented below:

- This paper presents a novel technique known as ensemble SVM and sample-weighted random forests (ESVM-SWRF) via Remora optimization to authenticate an individual using the Gait cycle.

- The efficiency of this methodology is evaluated using the CASIA-C dataset using different performance metrics for diverse walking speed changes like normal, fast, and slow walk.
- The proposed methodology offers improved robustness in terms of gait authentication, error rate, and rank when compared to different state-of-art techniques for different speed.

This article is structured in the following manner. Few research works based on the authentication of Human Gait using various mode of approaches is presented in *section 2*. The *section 3* elaborates the ESVM-SWRF technique in detail for human gait authentication. The comparative analysis of the proposed method's accuracy with other existing methods is discussed in *section 4*. The conclusion and future directions of the paper is deliberated in *section 5*.

2. REVIEW OF RELATED WORKS

Papavasileiou et al. [11] presented Gait based continuous authentication (GBCA) method by implementing wearable sensor and multimodal learning. This technique required some sort of coordination from the user side for an efficient human movement. The database was collected from different case studies one from medical grade research pattern of smart shoes and the other one from smart sock's commercial off-the-shelf. The smart shoe and smart socks were detected with minimum error rate of 0.16% and 0.01%. Khan et al. [12] introduced vision-based approaches (VBA) for the authentication of person through Gait biometric. In this approach, the users do not have compulsion to walk in prescribed pattern in predefined manner and authentication is carried out without human consent. In this method the Gait's biomechanics were calculated by variety of feature and also based on the performance compatibility they have arranged into various classes and subclasses. This method was a time-consuming process. The concept based on convolutional neural network (CNN) was explained by Ambika et al. [13] to determine the speed invariant HGA (human gait authentication). This CNN algorithm has organized the Gait with considering the speed deviation. The database was obtained from CASIA of CBSR (center for biometric and security research). A variant in Gait authentication namely Silhouette based method which has considered as an efficient technique in Gait authentication and it has better adequacy. The accuracy obtained in the classification process was 99.3%. Arora et al. [14] proposed a gait biometric using the Gait Information Image (GII) features technique. The researcher used various datasets like the Casia-B dataset, SOTON, OU-ISIR Treadmill B database, OU-ISIR Treadmill A database to test the gait features. The Nearest Neighbor (NN) classifier is used to evaluate the performance of the proposed method. He derived Energy Features (EF) and Sigmoid Features (SF) from GII to check the human walk in normal conditions and different conditions. The state-of-art work is proved efficient performance because GII tested every pixel of the image features using the information set Zulcaffle et al. [15] Proposed a gait recognition using a 3D Time of Flight (ToF) camera. This method uses four optimization algorithms like human silhouette extraction algorithm, gait cycle algorithm, new 3D gait image representations, novel Adaptive Multi-Stage Fusion Classifier. This method can be used in the corridors of the airport and train terminals for security purposes. It will work well in non-time conditions. The 3D-based feature will affect time-based variations, so in the future 2D feature should be developed and combined with 3D for better performance during the time-variant conditions. Godiyal et al. [16] proposed a gait authentication based on criteria like heel strike (HS) and toe-off (TO) during over-ground (OG) and ramp walking was determined using Force Myography (FMG) signals. The dataset was collected from 5 adult men by wearing a wireless Force Myography (FMG) data acquisition system on the thigh, thereby collecting the information regarding the walk. The proposed system is less expensive, simple to develop, and friendly to wear.

3. PROPOSED SVM-SWRF FOR HUMAN GAIT AUTHENTICATION USING REMORA ALGORITHM

The proposed architecture for Gait authentication is presented in *figure-1* and initially the input images form CASIA-C database is taken for gait cycle estimation. The features from the gait images are extracted and classified using the SVM-SWRF ensemble optimized using the RO algorithm. Based on the individual gait cycles, the individual is authorized and granted access. The working of the proposed methodology is explained in the subsections.

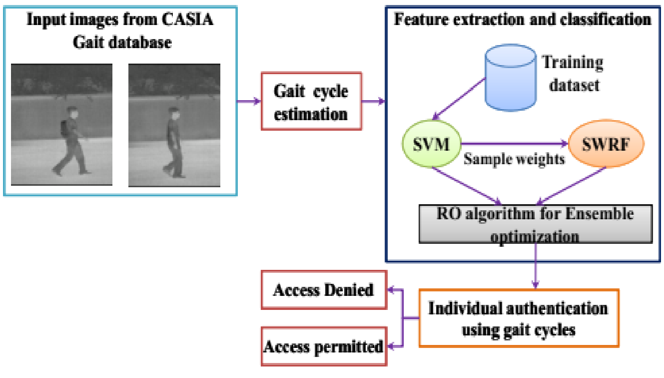

Figure 1: Proposed architecture for gait authentication

3.1 Gait cycle estimation

Gait is the periodic nature of walking in which the periods are measured by means of simple approach [17]. The gait period is calculated by considering the bottom half part of human silhouettes because the bottom part depicts most dynamic area. The gait cycle is calculated by counting foreground pixels. In addition to this, the gait cycle is comprised of two stride phases; they are stance and swing. The walking style represents one foot at stance and another foot as swing. Two continuous stance phases make one complete gait cycle. If the two legs are placed at maximum distance, the foreground pixels reach local maximum points and if the two legs are overlapped, it attains local minimum. The gait cycle is measured by leaping each second peak from three peaks [18, 19, 20].

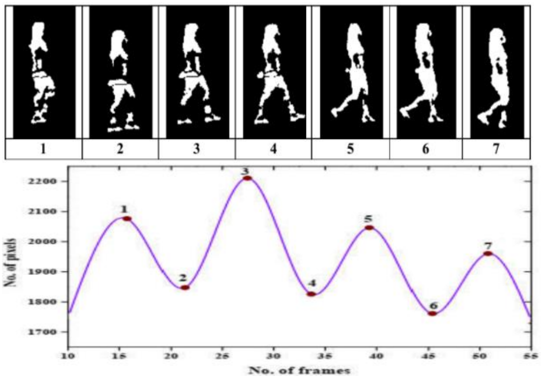

Figure 2: Local maximum and local minimum of human silhouettes with respect to varied foreground pixels

Figure 2 represents the local maximum and local minimum of human silhouettes with respect to varied foreground pixels.

Based on the information-based features of one complete gait cycle, the Gait information image (GII) is calculated from the normalized and centralized silhouette images. After setting the image dimension, Gait information image is measured for every image pixels. In a specific pixel location, the input data set will be generated from silhouettes intensity values. The gait features are separated from GII by means of information set. Assume that the information set $\{J_{xy}\eta_{xy}^{k}\}$ containing some information values. The superscript is dropped from the information set for generalization and only the $\{J_{xy}\eta_{xy}\}$ values are considered. In this, every information values of $\{J_{xy}\eta_{xy}\}$ are considered as information unit.

Information set function: The development of diverse information sets is easier by changing the information source and agent values. Thus, the gait information image with sigmoid feature is formed by modifying the information source values and also the gait information image with energy feature is formed by modifying the agent values.

GII with energy features: The generalized Hanman-Anirban entropy function is utilized for the generation of energy features. The numerical expression for the GII based energy feature is given as follows,

$$Q = \sum_{x=1}^{N}\sum_{y=1}^{N} R_{x,y}e^{-(pQ_{xy}^{3}+qQ_{xy}^{2}+rQ_{xy}+s)^{\beta}} \quad (1)$$

From the above equation, $e^{-(pQ_{xy}^{3}+qQ_{xy}^{2}+rQ_{xy}+s)^{\beta}}$ represents the polynomial exponential function with a power β. By modifying β and by setting the information source set, the varied information sets are formed. Let us consider β is equal to 2 and the other components are fixed as same, then the energy feature is obtained as,

$$Q_1 = \frac{1}{N}\sum_{x}\sum_{y} J_{xy}\eta_{xy}^{2} \quad (2)$$

The term J_{xy} denotes the normalized intensity value and η_{xy}^{2} depicts the Gaussian function. The squaring of agent minimizes the weights in information sources thus decreasing the uncertainty and increasing the efficiency of result.

By using generalization approach, it is easier to obtain energy features meanwhile the simple entropy function is accomplished bi-directionally. In this, initially the information values are gathered then the values are applied. The two-way steps of energy feature are derived as follows,

$$Q = \frac{1}{N}\sum_{x}\sum_{y} J_{xy}\eta_{xy} \quad (3)$$

Substituting $J_{xy} = Q_{xy}$ we obtain

$$Q = \frac{1}{N}\sum_{x}\sum_{y} Q_{xy}\eta_{xy} \quad (4)$$

Where, $Q_{xy} = J_{xy}\eta_{xy}$. This energy feature results determine the uncertainty of information source values by means of original agent η_{xy}.

GII with sigmoid features: The information value $J_{xy}\eta_{xy}$ is integrated with sigmoid function in order to provide sigmoid features. The mathematical expression of sigmoid feature is illustrated as follows,

$$Q_2 = \frac{1}{N}\sum_{x}\sum_{y} \frac{T_f}{1+e^{(-J_{xy}\eta_{xy})}} \quad (5)$$

The term $T_f = \frac{1}{M}\sum_{y=1}^{M} J_{1y}$, M=N= sum of frames in one complete gait cycle.

3.2 Ensemble support vector machine and sample weighted random forest (ESVM-SWRF) optimization

SVM is a classification algorithm which is widely used for pattern recognition and mainly utilized in biological applications [21]. Conventional techniques reduce the empirical risk factors but the SVM approach reduces the structural risks. In order to increase the two class margin, the hyper plane is determined by the SVM. It consists of several support vectors which lay on the margin and the hyperplane which positions on the middle of two classes. SVM creates a trade off in decreasing classification error and increasing margin but it is maintained by the parameter D. SVM also establishes kernel function to extend the data from low to high dimensional. It was made to handle the non-linear classification difficulties in low dimensioned space. The supervised machine learning RF method is widely utilized in biological application which is built from decision tree algorithms. The random forest algorithm

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integrates many decision trees for classification process. On training, every split determines the optimal features from the subset arbitrarily. Moreover, until training, the trees are trained without post pruning. Post pruning facilitates the trees to classify the training set accurately. After training, RF considers or takes the majority votes or average from each split. The parameters such as number of trees required for growing, minimum node dimension for splitting and variable numbers to randomly select every split decisions are taken into account when training RF. The overall performance of SVM and RF gets decreases when the training dataset subjected to class imbalance. So, in order to address this issue, the ensemble method called *ESVM-SWRF* is proposed which incorporates both the SVM and sample weighted random Forest algorithms. The training dataset samples are trained initially by SVM and then the score of each sample is predicted. Depending upon the predicted scores, specific weights are allotted to every sample.

Next, the samples are trained under SWRF and thus unseen query samples are determined. This ESVM-SWRF ensemble method enhances the overall performance. The training phases of proposed method is sub-divided into four levels; they are described as below,

3.2.1 SVM training based on each sample

The whole training dataset such as $C_{min} \cup C_{maj}$ is trained based on the SVM model. Where, D and $kernal_p$are the prescribed parameters. While the SVM training on the imbalance dataset, a lower cost to the majority class (min) and the higher cost to the minority class (maj) is assigned.

3.2.2 Sample weight calculation to each sample

Feed each training samples to the corresponding score and trained SVM once the SVM model is trained. Assign the weights to all training samples. For the minority sample class, the following equation defines the sample weight function.

$$Min_W(X) = \frac{1}{|C_{min}|} \times \frac{1}{1+e^{scale(SVM(X)-max\,ms)}} \tag{6}$$

Equation (6) defines the majority class sample with its weight function.

$$Maj_W(X) = \frac{1}{|C_{maj}|} \times \frac{1}{1+e^{scale(min\,ms-SVM(X))}} \tag{7}$$

The trained SVM predicts the sample score X is $SVM(X)$.

3.2.3 Sample weighted RF training

Obtain the weight of samples depending upon the raining dataset $C_{min} \cup C_{maj}$ and the sample weighted RF (SWRF) is trained. The number of variables to choose at random for each decision split, minimal node size to split and the number of trees to grow are the three major parameters need to be preset.

3.2.4 Return a trained sample weighted RF

The averaging outputs of SWRF and SVM achieve the final SSWRF model, it is expressed as below:

$$S_{SWRF} = \frac{(SWRF(X)+SVM(X))}{2} \tag{8}$$

3.3 Remora Optimization (RO) algorithm

In the Family Echeneidae, the eight species of marine fishes are described via sucker, diskfish, suckerfish and remora [22]. Remora optimization (RO) algorithm is used to minimize the time complexity of multi-thresholding model. The search space problems are denoted by using the R dimensional remora location and deem the optimal solution. Fast swimming varies the position of remora and its location is $R_i = (R_{i1}, R_{i2}, \dots \dots R_{iD})$. The search space dimension is DI based on i^{th} remora. From this, $OP_R = (R_1^*, R_2^*, \dots, R_d^*)$ is the search space with respect to the optimal solution and $fit(OP_R) = fit(R_1^*, R_2^*, \dots, R_d^*)$ is the optimal fitness function. The following section explains the remora behavior of ROA such as free travel or exploration and eats thoughtfully.

3.3.1 Exploration –Free travel

Two major key points of free travel or exploration steps are SFO concept and attack experiencing.

- ***SFO concept***

The attachment of swordfish updates the remora location. The below equation is used to update the position of remora.

$$R_i^{t+1} = OP_R^t - (rand(0,1) * \left(\frac{OP_R^t + radoim_R^t}{2}\right) - randoim_R^t \tag{9}$$

Here, *t* represents the ongoing iterations and the maximum number of iterations is denoted as T. $randoim_R$ is the randomly selected position of remora. Both ongoing and maximal iterations are performed by representing as *t* and *T* with the remora random position is $randoim_R$. The fitness value randomly chooses the remora in which the attack experiencing phase provides current iteration fitness.

- ***Experience attack***

Equation (10) computes the host variation of remora.

$$AE_R = R_i^t + (R_i^t - PV_R)^* randn \tag{10}$$

From the above equation, PV_Rrepresents the previous generation position and AE_R is the tentative step. The below equation expresses the current solution fitness, which is smaller to attached one.

$$fit(R_i^t) < fit(AE_R) \tag{11}$$

3.3.2 Exploitation or Eat Thoughtfully

The exploration step included both Whale Optimization Algorithm (WOA) strategy and host feeding.

- ***WOA concept***

The following equation formulates the remora attachment as well as the updating position of whale.

$$R_{i+1} = distance * e^{\delta} * \cos(2\pi\gamma) + R_i \quad (12)$$

$$\gamma = random(0,1) * (A - 1) + 1 \quad (13)$$

$$A = -\left(1 + \frac{t}{T}\right) \quad (14)$$

$$distance = |OP_R - R_i| \quad (15)$$

The current prey and hunter location distance is $distance$. Under the interval of [-1,1] and [-2,-1], the selected random number is γ.

- ***Host Feeding***

It is the subsection in the exploitation stage. The solution space of this stage can be mitigated to the position space of the host. It can be formulated as,

$$R_i^t = R_i^t + D \quad (16)$$

$$D = s * (R_i^t - c * OP_R) \quad (17)$$

$$s = 2 * U * random(0,1) - U \quad (18)$$

$$U = 2 * \left(1 - \frac{t}{maximum\ iteration}\right) \quad (19)$$

Where, *D* denotes the small step of movement and the remora location is *s*.

Based on the classification results an individual is authorized using their gait cycle such as normal, fast, and slow walk. The authorized personnel is granted access whereas the unauthorized user is denied access.

4. RESULT AND ANALYSIS

CASIA-C was collected by an infrared camera in July August 2005. It contains 153 subjects with 4 different walking conditions. There are four speed variations in the CASIA-C dataset along with backpack carrying condition. Besides the video files, we are provided with human silhouettes extracted from video files [23].

Figure 3: Representation Images from CASIA-C dataset

Table 1 explains the comparative analysis of different state-of-art methods with our proposed method to show the variations concerning speed in the gait cycle. The proposed method shows good performance when the walking speeds are the same. Our method shows efficient performance even the speed changes when compared to other methods.

Table 1: Comparison of robustness for variations in the gait cycle (with respect to the speed of walk) using different methods

Methods	CNN	GBCA	VBA	GII [1]	ToF [2]	FMG [3]	Proposed Method
(slow, slow)	95	100	100	100	100	100	100
(fast,fast)	94	98	100	95	94	99	100
(fast,slow)	-	84	80	85	86	82	88
(slow,fast)	70	75	79	74	78	75	92

Table 2: Comparison of Speed Gait performance (%) of different methods with the proposed method using Casia-C database

Speed Variance		DCM [4]	The Proposed Method
Minimal Variance	Training set	84	100
	Test Set	96	96
High Variance	Training Set	64	80
	Test Set	52	84

In *table 2*, the speed variance of an existing and the proposed method is shown. These two methods use the same dataset CASIA-C but when comparing both for minimal and high-speed variance, the proposed method shows efficient performance. The proposed method is also good in high-speed variance compared to state-of-art work.

Table 3 shows that as the number of training sets increases then the rank identification accuracy also increased.

Table 3. Relationship between training subjects and identification accuracy

Number of training	ERR(%)	Rank Identification (%)
10	11	57
20	10	60
50	9	68
100	7	72
125	6	75
150	6	80

The *figure 4* shows the accuracy rate of our proposed work concerning different walking conditions. For a normal walk proposed work shows 98% accuracy, for a slow walk it shows 82% accuracy, for a fast walk it shows 95% accuracy, for a walk carrying backpack it shows 80% accuracy, overall our proposed work shows 89% accuracy. It proves that our proposed work shows high accuracy compared to other methods.

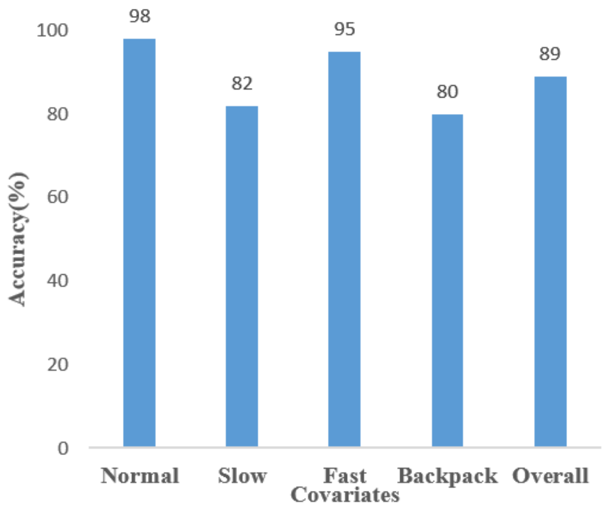

Figure 4: Relationship between the covariates and corresponding accuracy for the proposed method

5. CONCLUSION AND FUTURE WORK

A novel ESVM-SWRF method for authenticating humans using a gait cycle has been proposed in this paper. The different covariates related to walking are analyzed and investigated. The walking speed of people may change due to the individual body structure, gender, and age thereby creating a complex situation. Based on the past decades, different perspectives with cross-speed gait authentication were suggested. The factors influencing the identification of gait are some of the covariate factors namely walking speed, injuries, walking surface, viewpoint, and clothing. Our proposed work uses an effective dataset CASIA-C. Most of the existing techniques achieved a nearly 100% authentication rate for normal walking conditions but their performance is not accurate when applied under different covariate conditions. But our proposed work proves a high accuracy rate for different covariate conditions compared to other existing methods.

Further analysis using large dataset is still required. Evaluating gait features like Frequency domain feature, Chrono-gait image using OULP dataset is future work.

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