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CHOG Based EFD for Geometric Shape Retrieval of Images for Cloth and Object Invariant Gait Recognition

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Abstract: ***Gait refers to person identification based on the observation of human walking style. One of the prominent hurdles in gait recognition is, the challenges posed by change in apparels like clothes and object held by the subject. The paper explores the feature extraction techniques like CHOG and Elliptical Fourier Descriptors in spatial and frequency domain respectively to mitigate this negative impact on gait recognition. The CHOG behavioural feature extraction technique is used to capture the effective distribution of local gradient on gait sequence images. Further the Elliptical Fourier Descriptor (EFD) is found in frequency domain to access the geometric characteristics of a spatial domain image. The work is carried out on 36 subjects with 5 different apparels and 3 different objects each with 6 gait cycles from standard dataset CASIA SET – B and CMU - MoBo. SVM classifier is used to effectively discriminate the gait cycle patterns using optimal hyper plane. The results obtained have given an improvement of 7% to 24% increase in gait recognition over earlier techniques like GEI, CDA, LDA, ENTROPY, static and dynamic region splitting.***

Key words – Circular histogram of oriented gradient(CHOG), Gait cycle, EFD, Silhouette.

I. INTRODUCTION

Gait is a challenging computer vision based signal processing technology, for biometric identification. The need for efficient biometric security system is a priority at places like malls, defence area, border crossings, airports, banks, public transport systems and at many private and public sector offices. The first generation biometrics like face recognition, palm recognition, fingerprint, iris and password entry requires permission and physical presence of the subject therefore it is not sufficient to analyse and track the suspicious movement or to trace out intruders. This has led to the second generation of biometric authentication method like Gait recognition system. The advantage of Gait is its capability to capture the biometrics of the people from far distance without their knowledge.

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Also gait of a person cannot be disguised or imitated, hidden, or stolen.In recent years the research community has started working on underlying challenges in gait recognition system like view invariance, cloth invariance, change in walking speed, shoe type and loading effects. Gait recognition approach can be classified into model based recognition system and motion based recognition system[1,2,3].One such limitation is imposed when people wear different apparels or hold any object, if the clothes worn are longer and covers the torso and limb, and then it becomes extremely difficult to identify and record the gait parameters of leg movements. Also holding an object effect the subject's body shape, in few cases it can even affect the way the subject walks. Due to this, clothes and holding of an object poses tough challenges to the researchers over other covariate factors like shoes type, carrying condition, view angle etc. The earlier researchers have mainly concentrated on getting solution using techniques like GEI, LDA, SRC method and Random sub space method in spatial domain [4-7]. This gives us the motivation to analyse the features effectively in frequency domain. Also, it gives the scope and opportunity to counter the challenge posed by cloth invariance using CHOG technique and elliptical Fourier transform on CHOG in frequency domain. CHOG helps to capture the regional local intensity gradient effectively. When the subject wears different cloth of different length, some time the gait movement gets hidden inside the cloth. In such situations the inner annuls of CHOG covers the mid section of the body where there is not much energy gradient movement. Hence most of the time the information in those region remains static across all the frames in the gait cycle, while the outer most annul covers the head and limb movement which is the dynamic energy component. Giving more weightage to the CHOG feature extracted from this annulresultsinto cloth and object invariant of gait recognition. Further to access the geometric characteristics of a spatial domain image, we go for frequency domain analysis. The elliptical Fourier transform decomposes spatial domain image into its sinusoidal components, which makes it easy to examine or process certain frequencies of the image that understand and analyse the behavioural changes of these local geometric structure over consecutive frames across the gait cycle in the spatial domain.

II.RELATED WORK

P.B. Shelke, P.R. Deshmukh[4] have proposed a method based on part of the body that contributes more towards the person identification on the basis of Rectangular Region developed based on Silhouette Analysis (RRSA) algorithm to evaluate the contribution of individual parts of the body to identify the person correctly.

This experiment is tested on CASIA dataset having 20 subjects using SVM Classifier.SoumabhaBhowmick, Anup Nandy, Pavan Chakraborty, G. C. Nandi [5] have proposed an approach on how different apparel worn by a subject impacts the behavioural feature of an individual locomotion. A computer based approach is applied to derive gait feature information and gait entropy image is extracted as a feature vector. A statistical based Naïve Baye's condition probability function is used as aclassifier using OU – ISIR dataset having 15 subjects with 16 types of clothes by each subject. Shiqi Yu, Daoliang Tan, Tieniu Tan[6] have proposed a method using three different sets of data A, B, C having normal walking sequence set, walking sequence with change of clothes and walking with various load carrying conditions respectively. Each set of data is taken by 11 different cameras at an angle of 18°.GEI is used as feature and standard deviation is a statistic used to validate the results. The experiment uses 124 subjects each image of size 320 x 240 at 25Gps tested on CASIA gait dataset.Abbas Ghebleh, Mohsen Ebrahimi Modhadam[7] proposed an idea of splitting the silhouette into 3 regions to isolate the negative impact of clothing in effected region. Silhouette is split into 3 regions with 15% of height set as threshold. This experiment is done using GEI feature extraction with 68 subjects having upto 32 cloth variations.

III. PROPOSED METHODOLOGY

The outline of proposed method is shown as a block diagram in fig 1. 36 subjects are considered with 5 different apparels (clothes) and 3 different objects from CASIA – B and CMU - MoBo standard datasets.In each subject for everyapparel, 4 gait cycles are used to train the system. Each gait cycle will have 16 image frames. Each image frame is pre processed to remove the background of the image, retain only the subject and extract itssilhouette as shown in fig. 3a. Theimage frame feature is extracted using CHOG technique in spatial domain and is further processed to find its elliptical Fourier descriptors as shown in fig. 3(c,d and e). These features are stored into the gallery and is tested against the query image.The classification is carried out using SVM classifier which is used to achieve better discriminativeinformation between multiple gait features by minimizing empirical classification error and by finding the optimal hyper plane WTX + b = 0 that leads to maximal geometric margin (γ).The geometric margin is $\gamma = \frac{1}{||W||} = \frac{1}{<W.W>}$ The SVM classifier is used with four kernel functions namely Linear Kernel function, Radial basis function, Quadratic function and Least square function.

A. CHOG

The Effective distribution of local intensity of the gradient is captured using the new variant of Histogram of oriented gradient called as CHOG. Circular HOG feature extraction process is shown in fig. 2. In this method each image frame of the gait cycle to be analysed is divided into multiple non overlapping annular circles, starting from the origin at the centre of the image. In turn each annular circle is divided into 4 non overlapping sectors called as cells. The gradient magnitude and its orientation for each cell is calculated using eq. 1,2,3&4. Further the L-2 normalization of the obtained feature is found using equation 5 on CHOG. The CHOG gradient magnitude vector (C-VECTOR) of the image is generated by collecting orientation gradients of each cell of the inner circular annuls followed by appending the orientation gradients of the next circular annuls till all the circular annuls completes.To find the CHOG feature vectors the first order directive high pass filter is used.In the image frame, let I(x,y) be the pixel value in the image. Let [-1,0,1] and $[-1,0,1]^T$ be the directive filter mask along x and y direction respectively, with which all the image pixels I(x,y) are convolved. The horizontal plane gradient and the vertical plane gradient of the pixel under consideration is found as shown in fig. 3b, by a measure of change in pixel values along X-direction and Y-direction around each pixel as shown in equations 1 and 2.

$$G\_x = I(x+1, y) - I(x-1, y) \quad (1)$$

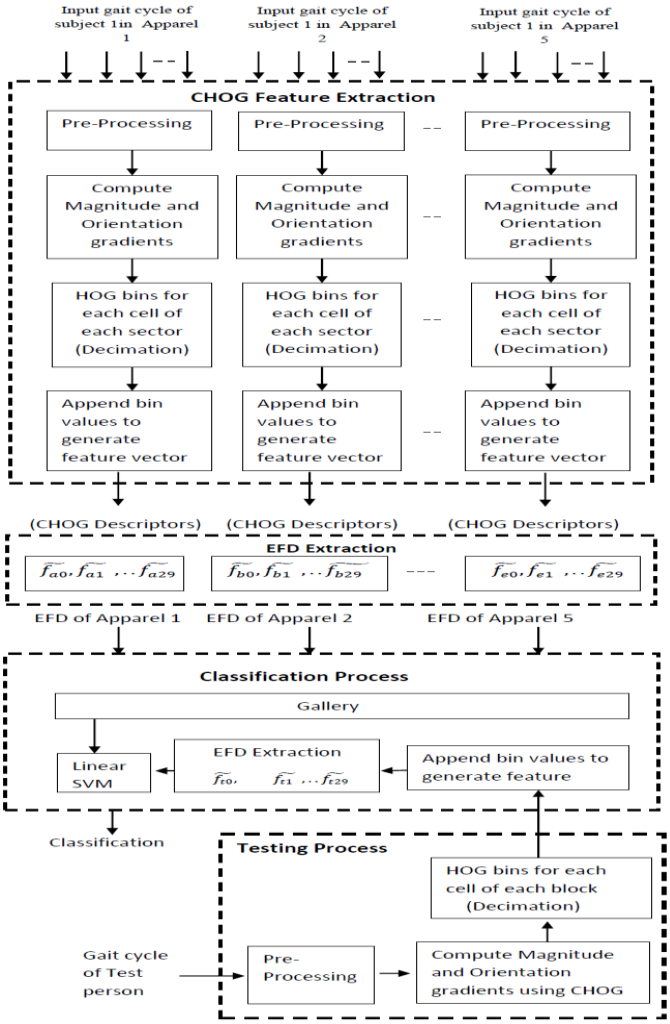


Fig. 1:Proposed Methodology for gait feature extraction and classification

$G\_y = I(x, y+1) - I(x, y-1)$ (2)

Where $I(x, y)$ is the pixel value of the image at the location (x,y).Then the magnitude of gradient at the pixel I (x,y), is given by

$$G = \sqrt{(G\_x)^2 + (G\_y)^2} \quad (3)$$

its angular gradient orientation is calculated using

$$G\_Angle = \arctan\left(\frac{G\_x}{G\_y}\right) \quad (4)$$

To keep the obtained magnitude gradient information illumination free, it is further normalized using L-2 normalization. This eliminates local contrast and brightness variation effects. The L-2 normalization is given as

$$Featurenorm = \sqrt{\frac{Feature}{\left(||Feature||_2^2 + e^2\right)}} \quad (5)$$

the length of the CHOG descriptor vector is given by

Fc=no. of annular circle ×no. of cells×no.of bins (6)

The CHOG's annuls can be matched with polar co-ordinate system in which the different annuls indicate various distance to the pole and orientation bin is indulged angle.

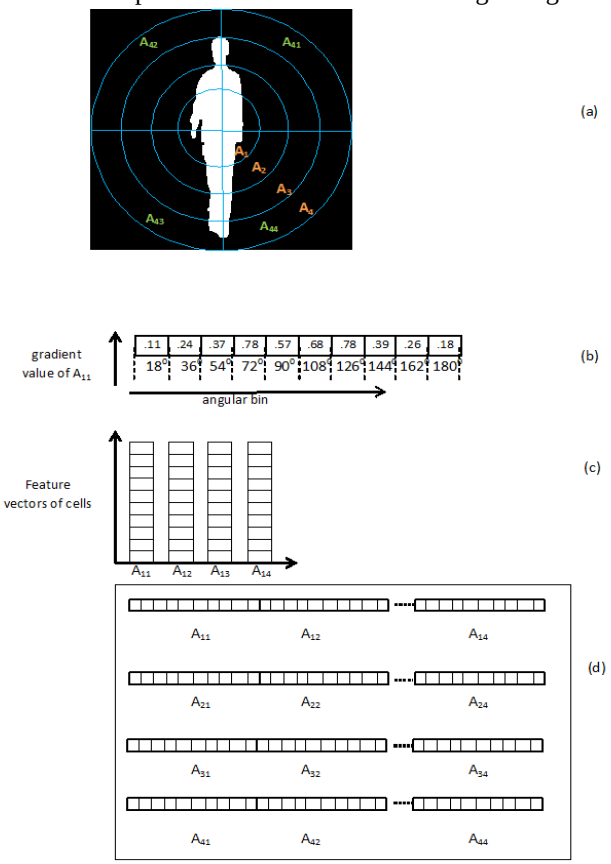


Fig. 2. CHOG descriptor extraction process. For given image with 4 annular circles and 4 cells in each annuli (a) , sample feature extraction of first annuli's first cell A_{11} with 10 bin values (b) , feature extraction of all 4 cells of annuli 1 i.e., A_{11}, A_{12}, A_{13}& A_{14} (c) , CHOG descriptor of all 4 annuli (d)

B. Elliptical Fourier descriptor

This gives close contour description, A closed curve which is a continuous periodic function can be represented as a sum of sine and cosine functions of growing frequencies. The sum of these sine and cosine functions converges at initial contour as the number of harmonics increases. Each harmonic is an ellipse completely defined by its period and it Fourier Descriptors. The equation used to transform the polar coordinate into Cartesian coordinates is given in equation 7,8 & 9.

$$x = r\cos(\theta), \quad y = r\sin(\theta) \quad (7)$$

Where (r, θ) are the coordinates in the polar system and (x,y) are the coordinates in the cartesian system and

$$r = (r0 + Feat\ (j \times k,\ i) \quad (8)$$

$$\theta = 2\pi\frac{2\pi}{sector-num} \times j + k \times \frac{2\pi}{sector-num \times bin-num} \quad (9)$$

where i, j, and k represent the location of the orientation k of cell j in annulus i, and r0 is a constant whose value depends on the application. The parameter r0 is used because the accumulated gradient magnitudes are very small. The elliptic Fourier transform is implemented on a complex plane, each pixel in the image is described as a complex number. The first coordinate denotes the real part, and the second coordinate denotes the imaginary part. The received Cartesian coordinate 'coord' can be described as follows

$$c(j) = x(j) + iy(j) \quad (10)$$

where x (j) , y(j) are the coordinate values.

To perform the elliptic Fourier transform, Equation must be expanded.The elliptic coefficients can be defined as

$$C(k) = c_{xk} + ic_{yk} \quad (11)$$

Based on the relationship between the coefficients in the form of the exponential function and the trigonometric function, the coefficients $c_{xk}$and c_{yk}in the trigonometric function can be defined as the discrete coefficients a_{xk} ,b_{xk} , a_{yk} , and b_{yk}.

$$a_{xk} = \frac{2}{m}\sum_{l=1}^{m} x(l)cos(kwl\tau)$$

$$b_{xk} = \frac{2}{m}\sum_{l=1}^{m} x(l)sin(kwl\tau)$$

$$a_{yk} = \frac{2}{m}\sum_{l=1}^{m} y(l)cos(kwl\tau) \quad (12)$$

$$b_{yk} = \frac{2}{m}\sum_{l=1}^{m} y(l)sin(kwl\tau)$$

where $x(l)$ and $y(l)$ are the values of the sampling points of the functions x(j) and y(j), m is the total number of sampling points, and w is the fundamental frequency, which is equal to T=2π, where T is the period of the function.The curve c(j) can be described as follows

$$c(j) = \frac{a_{x0}}{2} + \sum_{k=1}^{\infty} (a_k \cos(kwj) + b_{xk} \sin(kwj)) + i(ay02+k=1\infty aykcos(kwj)+byksin(kwj))(13)$$

In matrix form it can be written as

$$\begin{bmatrix} x(j) \\ y(j) \end{bmatrix} = \frac{1}{2}\begin{bmatrix} a_{x0} \\ a_{y0} \end{bmatrix} + \sum_{k=1}^{\infty} \begin{bmatrix} a_{xk} & b_{xk} \\ a_{yk} & b_{yk} \end{bmatrix} \begin{bmatrix} cos(k\omega j) \\ sin(k\omega j) \end{bmatrix} \quad (14)$$

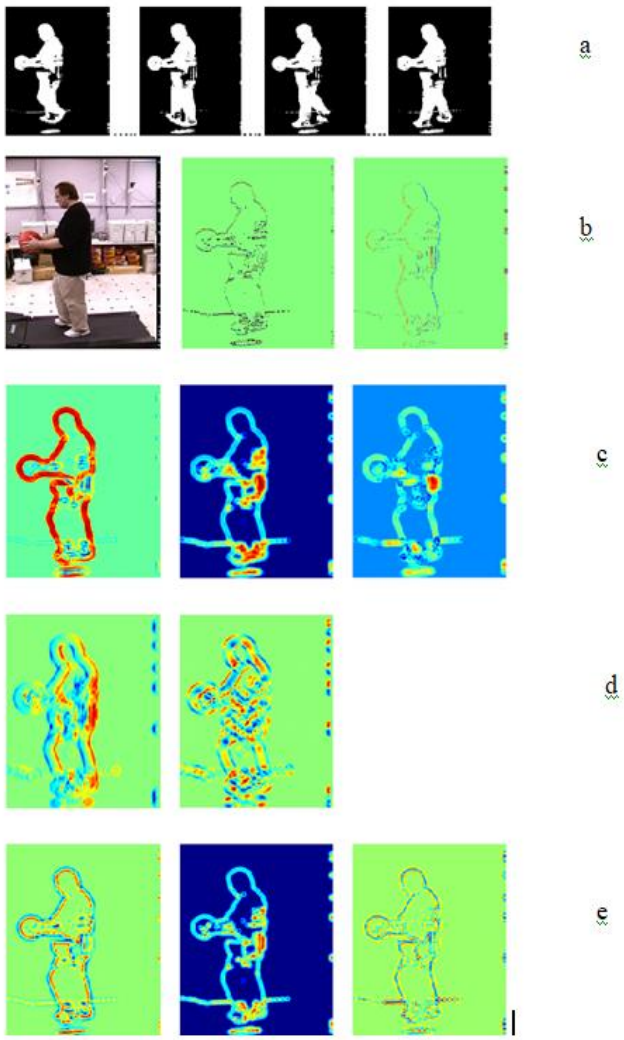


Fig. 3: Pre processing and Elliptical Fourier feature extraction. (a) Background subtraction and silhouette extraction of subject 1 holding a ball ,(b) CHOG feature of x and y direction gradient, (c) Sample regional Elliptical Fourier Descriptors, (d) Sample real and imaginaryElliptical Fourier Descriptor, (e) Sample rotation invariant Elliptical Fourier Descriptor For each item in equation (13), if k has a fixed value, the sum of the trigonometric functions defines an ellipse in the complex plane. Assuming a change in j, the point will move along the ellipse at a speed that is proportional to the associated frequency k, where k is the number of circles that pass through this point. Each spindle of the ellipse is calculated using ak and bk . If ρ is the rotation angle, the coordinate values are as follows

$$\begin{bmatrix} x'(j) \\ y'(j) \end{bmatrix} = \frac{1}{2}\begin{bmatrix} a_{x0} \\ a_{y0} \end{bmatrix} + \begin{bmatrix} cos(\rho) & sin(\rho) \\ -sin(\rho) & cos(\rho) \end{bmatrix} \sum_{k=1}^{\infty} \begin{bmatrix} a_{xk} & b_{xk} \\ b_{yk} & b_{yk} \end{bmatrix} \begin{bmatrix} cos(k\omega j) \\ sin(k\omega j) \end{bmatrix} \quad (15)$$

III. EXPERIMENTAL RESULTS AND ANALYSIS

A. Experiment 1

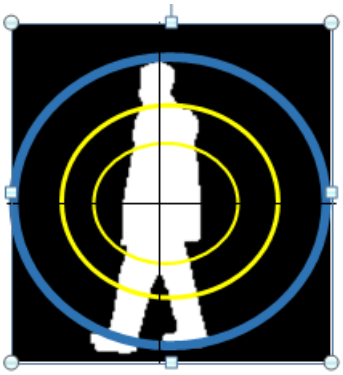


Fig.4: CHOG feature extraction on sample silhouette of the subject wearing coatconsidering only 3rd annul.

Table- I : Gives effectiveness of CHOG feature with different number of annuls.

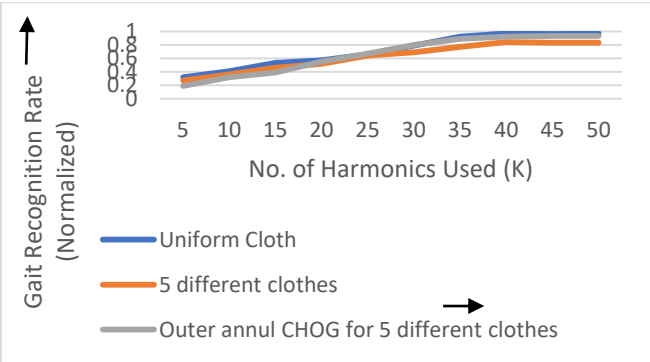
CHOG annuls considered for feature extraction		Normal gait recognition rate (%)	Gait recognition rate with 5 different clothes (%)	Gait recognition rate with 3 different objects (%)
All 4 annuls (fig. 3)	CHOG	96.2	40.2	39.9
	CHOG +EFD	98.7	52.3	40.1
4th annul only (fig. 3)	CHOG	88.0	79.7	69.1
	CHOG +EFD	91.3	82.7	68.4
3rd and 4th annuls of 4 annuls (fig. 3)	CHOG	93.4	73.5	80.1
	CHOG +EFD	95.3	72.7	80.9
3rd annul of 3 annuls (fig. 4)	CHOG	92.0	84.3	78.3
	CHOG +EFD	95.3	87.3	81.5

This experiment is carried out to understand and analyse the effectiveness of CHOG technique and EFD technique on gait invariant approach.

The experiment is performed on CASIA dataset B and CMU – MoBo . 36 subjects with 5 different clothes and 3 different objects are considered in which each gait cycle has 16 frames of 128 x 256 resolution. For each subject 4 gait cycles were used for training and other 2 gait cycles were used for testing. The CHOG feature extraction highlights the effective distribution of local intensity gradient that helps us trace the small interframe gradient movement. In CHOG representation the gait images are represented with different number of annuls, and to find its effectiveness the CHOG feature extraction is done as shown in table 1. The Table shows the observed results for CHOG image representation with different cases of 4 annuls and 3 annuls. The gait recognition rate increases with increase in number of annuls for normal gait sequences and it gives the best results with 4 annuls. As the cloths start changing, for the given subject the 3 annul image representation gives good recognition rate, this is because the 3rd annual can capture all dynamic features of leg movement and covers the head image features. While the negative impact of the subject changing the cloths or holding an object can easily be negated by ignoring 1st annul and 2ndannul feature and by considering only the 3rd annual. So by smartly choosing number of CHOG annuls we can discriminate the dynamic gradient region from that of static. Further the table also shows how the EFD 0f CHOG features can further increase the recognition rate by extracting the structural geometric shape of the gait.

B. Experiment 2

As the harmonics of EFT increases the gait recognition accuracy increases. Elliptical Fourier Descriptors for 'X' aspect of the shape are given by function $a_{xk}b_{xk}$ .Similarly the Elliptical Fourier Descriptors for 'Y' aspect of the shape are given by function $a_{yk}b_{yk}$ To quantify each harmonics it requires four terms ($a_{xk}b_{xk}a_{yk}b_{yk}$) .These 4 terms of Elliptical Fourier spectrum calculated over a series of harmonic amplitude (k) are sufficient to represent any form of gait image shape to the desired level of accuracy. The number of harmonics necessary to represent the gait more accurately depends on the point where empirical outline deviation can be minimized. The graph 1 shows the accuracy of gait identification with respect to number of harmonics used to define it. Smaller the harmonics, poorer the geometric shape defined and as the number of harmonics increases,the



Graph 1 : Shows Gait recognition accuracy v/s Elliptical Fourier Descriptor Harmonics

Geometricshape characteristics increases leading to an accurate gait identification. In this experiment the threshold has reached at 40 number of harmonics (40 x 4 = 160 terms). If harmonics is reached beyond this, the accuracy remains unchanged.

C. Experiment 3

Table- II: Performance of proposed methodology over other reported methods on OU – ISIR and CASIA – B dataset

Methodology	Data set	Normal Gait dataset (%)	Holding different objects (%)	Different clothes (%)
GEI + CDA	CASIA-B	99.4	60.2	30.0
GEI + LDA	CASIA-B	96.0	69.3	59.7
ENTROPY	OU - ISIR	--	--	84.0
CHOG	CASIA-B	96.0	84.3	82.7
CHOG + EFD	CASIA-B	97.7	92.4	90.3
OUTER CHOG ANNUL + EFD	CASIA-B	89.0	93.1	91.1

The GEI, CDA, LDA, Entropy methods are earlier reported in literature for cloth invariant approach in spatial domain which gives the accuracy rate between 30% - 69%. The proposed method for the same gives much better recognition rate between 82% - 93% for CASIA – B dataset with different clothes and objects as depicted in Table2.

IV. CONCLUSION

Various experiments were carried out to analyse and derive better approach which is efficient against negative impact on gait recognition of subject co variate factors like different clothes and the objects held. In experiment A, the effectiveness of CHOG with different number of annular sections on gait recognition was tested for three different cases namely., I. Normal gait II. Different clothes III. Different objects held. In case B, the results show that the CHOG with 3 annular section with weightage given only to the third annul gives better recognition rate of 84.3% for subjects with different clothes. Further EFD employed on this annul gives the best gait recognition with 87.3% as the region of interest, i.e., head and leg movement are covered under annul 3 and the body part with different clothes covered in annul 1 and 2 is not considered for feature extraction. In case C, the gait recognition rate for subject with different objects held is better when CHOG with 4 annular sections in which the weightage is given to the 3rd and 4th annuls only is considered in spatial domain. Experiment B shows that with a smaller number of EFD harmonics the geometrical shape of the gait image cannot be captured perfectly but as more number harmonics are included the geometry of gait image is better obtained and at 40 number of harmonics the best geometry of the gait image is obtained. Further increase in harmonics will not contribute to the shape of the image. Table 2 gives the comparison of previous work found in literature with the proposed work.

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