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Effective part-based gait identification using frequency-domain gait entropy features

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Abstract Gait identification task becomes more difficult due to the change of appearance by different cofactors (e.g., shoe, surface, carrying, view, and clothing). The cofactors may affect some parts of gait while other parts remain unchanged and can be used for recognition. We propose a robust technique to define which parts are more effective and which parts are less effective for cofactors like clothing, carrying objects etc. To find out the effective body parts, the whole body is divided into small segments where each segment is a single row in this paper. Based on positive and negative effect of each segment, three most effective parts and two less effective parts are defined. Usually, the dynamic areas (e.g., legs, arms swing) are comparatively less affected than static areas (e.g., torso) for different cofactors in appearance based gait representation. To give more emphasis on dynamic areas and less on static areas, frequency-domain gait entropy termed as EnDFT representation is computed

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and used as gait features. Experiments are conducted on two comprehensive benchmarking databases: The OU-ISIR Gait Database, the Treadmill dataset B with clothing variations and CASIA Gait Database, Dataset B with clothing and carrying conditions. The proposed method shows better results in comparison with other existing gait recognition approaches.

Keywords Gait · Identification · Effective part · EnDFT

1 Introduction

Biometric person authentication has recently gained considerable attentions for a variety of applications such as access control and smart login systems. Biometric cues mainly fall into two families: physiological cues (e.g., fingerprint, finger vein, iris, face) and behavioral cues (e.g., eye movement, online signature). Human gait is one of such behavioral biometrics and has the following characteristics: (1) gait can be recognized even at low image resolution, namely, at a distance from camera [7, 17], while the other biometrics like face, iris, fingerprint etc. required relatively high image resolution for person authentication, (2) gait can be available without subject cooperation because gait as unconscious behavior is authenticated, and (3) gait as unconscious behavior is difficult to be spoofed.

Thanks to the above characteristics, scopes of the gait identification are ranging from video-based wide-area surveillance [21, 26] (e.g., finding terrorists or suspects in squares, stations, airports, banks, and car parking area) to criminal investigation (e.g., authenticating a perpetrator at a crime scene and a suspect in a street). In addition, potential application fields of the video-based gait analysis are ranging from health science (e.g., detecting the postural disorder or fallers to be) to sport science (e.g., providing the optimal technique strategies in sports training).

Such gait recognition techniques can be divided into two main categories: model-based and model-free (appearance-based) approaches and we refer the readers to surveys or books [9, 24, 25] for thorough introduction to individual approaches.

The model-based approaches use a priori knowledge of the human gait, more specifically, extract the gait features such as shape and motion by fitting the human model to input images. These gait features contain kinematics of leg motion by Fourier analysis [34], static shape parameters and gait period with an articulated body model [30], joint angles with an articulated body model [29]. Hee et al. [14] constructs a $2D$ stick model based on human anatomical knowledge [10]. More recently, Ariyanto and Nixon [1] propose a marionette mass-spring model for $3D$ gait recognition as a more mechanical model.

Model-based methods have limited efficiency because of the high computational burden on the basis of complex matching and searching. These methods also often suffer by model fitting errors. In fact, the study [31] reports that high quality gait image sequences are required to achieve a high accuracy.

Model-free approaches [3, 32] are comparatively insensitive to the quality of gait silhouettes and have the benefit of low computational costs compared to model-based approaches. These types of approaches outperform the model-based methods in general, which is the main reason why the most of the gait recognition approaches adopt the model-free approaches.

However, significant change in appearance due to different cofactors makes the model-free gait recognition problem much more difficult. Gait can be affected by different cofactors such as changes in clothing, viewing angle, elapsed time, walking surface, shoes, carrying objects etc. The gait signature is composed of different body parts. The effects of

different cofactors (e.g., clothing, carrying objects, viewing angles, surfaces, etc.) do not change all body parts. It may alter some parts of whole gait where other parts that are useful for gait identification remained unchanged.

Generally, for the whole-based methods[1], significant numbers of training subjects are required for representing the variation of full-body gait features, while relatively small number of training subjects will cover such variation of part-based gait features due to its low dimensionality. With regard to the different gait representation techniques there is still a major issue to define the effective body components that influence the gait recognition under the effect of different cofactors. Although a variety of part-based techniques [6, 13, 17, 18] have been proposed, the body parts are manually pre-defined in all the studies. Therefore, they did not provide any insights into the way how to define and select the effective parts from the whole human body under the effect of different cofactors.

From our point of view, there are two important ways to improve the recognition accuracy in case of different cofactors like clothing, carrying objects, etc.:

1. Gait features should be represented with the most discriminating information.
2. For selecting the appropriate parts, more affected and less affected body parts should be considered.

From these observations, for giving more emphasis on dynamic areas and less on static areas, the DFT based entropy (EnDFT) gait representation is computed from frequency domain gait representation. Then, a robust technique is proposed to define which parts are less affected by cofactors or more effective, and which parts are mostly affected or less effective. Based on the experimental result, we define three most effective body parts and two less effective parts. We use these three most effective body parts with the entropy based gait representation for gait recognition. Experimental results show better performance compared with the others part-based and whole-based approaches.

This paper is organized as follows: related works are discussed in Section 2. Section 3 provides different gait representation techniques including proposed frequency domain gait entropy feature. Section 4 discusses the part definition and selection procedure from frequency domain gait feature. Effective part-based feature extraction and classification techniques are found in Section 5. Datasets, all the experimental results and discussion are presented in Section 6 followed by conclusion in Section 7.

2 Related works

2.1 Whole-based approaches

Model-free methods [3, 32] consider gait features as a sequence of body posture and usually use silhouette to represent gait for measuring the similarity of body poses. Sarkar et al. [28] propose a direct silhouette sequence matching as a baseline method. Cuntoor et al. [8] project the silhouette into a width vector and Liu et al. [19] project it into a frieze pattern, namely, combination of width and height vectors. Self-similarity plots were used for gait recognition in [5]. Considering the periodic property of gait, a discrete Fourier transform (DFT) [22] is computed as pixel-by-pixel amplitude spectra of zero-, one-, and two- times

[1] We mean a method of directly matching the whole human body without any part selection by a term "whole-based methods.

frequency elements. Gait recognition using average silhouette is proposed in [20]. Han et al. [12] proposed the simplest yet the most prevailing baseline algorithm by just averaging the silhouette value pixel-by-pixel over the gait period, known as gait energy image (GEI). As a variant of the GEI, a gait entropy image (GEnI) [2] is computed as pixel-by-pixel entropy of the GEI so as to focus on dynamic regions. A gait flow image (GFI) [16] focuses more directly on the dynamic components, where the optical flow lengths observed on the silhouette contour are averaged over the gait period.

The entropy transformation of gait GEnI from GEI gives more weights in dynamic areas and less in static areas. In GEnI, dynamic areas show more uncertainty and thus more informative than static areas in gait representation. The DFT representation of gait shows better result than GEI for its separated two dynamic higher frequency components. The one- and two-times frequency elements in the DFT hold only the uncertainty values of the gait. Therefore, the entropy-based transformation of the DFT clearly separates the most uncertainty areas by adding one- and two- times frequency components to the GEI.

2.2 Part-based approaches

Various studies on human body components [6, 13, 17, 18] suggest that the combination of body parts may increase the recognition accuracy only when it is possible to separate the discriminating and over-fitting parts. The first methods that divide the human body into components for gait identification is described in [17]. They considered each component separately and applied in both person identification and gender classification. Boulgouris et al. [6] proposed a component-based gait recognition that considers the unequal discrimination ability of each part. In [18], seven gait components are defined. The contributions of the components have been studied both individually and in certain combinations for both human gait recognition and gender recognition.

A part-based gait identification method is proposed in [13]. The human body is divided into eight parts based on anatomical statistics. This method can reduce the effect of different clothing combinations by assigning higher weights to the unaffected body parts than the affected areas.

Avoiding the least reconstruction error, recently a random subspace method (RSM) is proposed [11]. Although the RSM outperforms other classical methods [12, 20], it does not guarantee the best accuracy for clothing-invariant gait recognition [15]. The method chooses N eigenvectors randomly from all the eigenvectors for creating L random subspaces.

3 Human gait representation techniques

To represent the gait features, most of the model-free gait recognition approaches use silhouettes. Silhouettes are extracted from each frame of a sequence by background subtraction. In prepossessing stage, each background-subtracted silhouette is registered to obtain the spatio-temporal gait silhouette volume (GSV) [22]. Then, the silhouettes are normalized into a fixed size of 128×88 pixel and calculate the normalized autocorrelation of a GSV to detect the gait period. Here, we shortly introduce some existing gait representation techniques below.

3.1 Gait energy image (GEI)

The spatio-temporal average silhouette over a complete gait cycle is called GEI [20]. Examples of GEI are shown in Fig. 1a. GEI represents both the static (head and body) and dynamic areas (swings of legs and arms) of the gait.

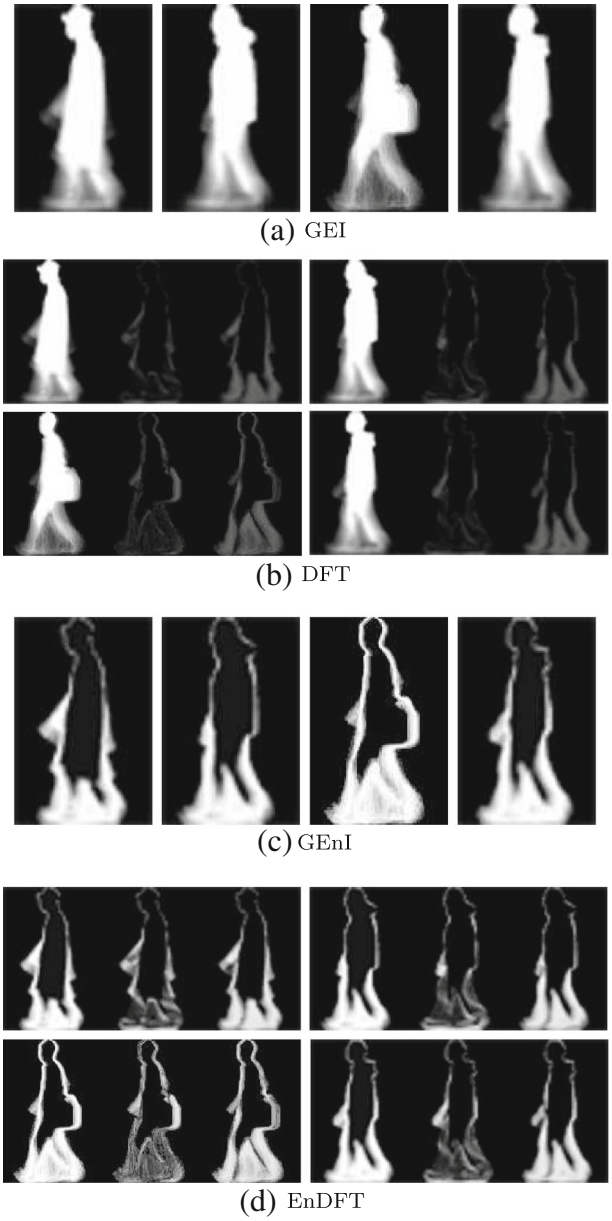


Fig. 1 Examples of (**a**) GEI, (**b**) GEnI, (**c**) DFT, and (**d**) the proposed EnDFT

Given the pre-processed binary gait silhouette images $B(x, y, n)$ at time n in a sequence, the GEI is defined as,

$$GEI(x, y) = \frac{1}{N}\sum_{n=1}^{N} B(x, y, n) \tag{1}$$

where N is the number of frames in a gait cycle, n is the frame number and x and y values are the $2D$ image coordinates.

3.2 Discrete fourier transform (DFT)

Another popular gait representation technique is the frequency domain gait features. The amplitude spectra of the GSV are calculated by DFT analysis based on the gait period [22] (Fig. 1b). A DFT $G(x, y, k)$ and amplitude $A(x, y, k)$ for the temporal axis are calculated as,

$$G(x, y, k) = \sum_{n=0}^{N-1} B(x, y, n) \exp^{-j\omega_0 kn} \tag{2}$$

$$A(x, y, k) = \frac{1}{N}\,|G(x, y, k)| \tag{3}$$

where N is the number of frames in a gait cycle, ω_0 is a base angular frequency for a gait cycle and k is the frequency component. Usually, only $0-2$ times frequencies are taken into account. Higher frequency elements are removed as noise. Therefore, DFT consists of three components where the first component is equivalent to GEI, middle component represents the asymmetry of the left and right motion and the last component represents the symmetry thereof.

3.3 Gait entropy image (GEnI)

In mathematics, entropy is used to measure the uncertainty of problems. While in information science, entropy is the average uncertainty of information source. In other word, entropy is a measure of irregularity of states such as imbalance, uncertainty like dynamic areas of human gait. If k symbols are generated from the source, then the average self- information obtained from k output is

$$-k\sum_{j=1}^{j} P(a_j) log P(a_j) \tag{4}$$

where a_j are symbols and $P(a_j)$ are source symbols probability. The average information per source output i.e., entropy is,

$$H(Z) = -\sum_{j=1}^{j} P(a_j) log P(a_j) \tag{5}$$

As $H(Z)$ increase means more information is associated with the source and if the source symbols are equally probable then the entropy will be the maximum. The intensity value of the binary silhouettes for a fixed pixel location as a discrete random variable, the entropy of this variable over each gait period can be computed as

$$H(x, y) = -\sum_{j=0}^{1} P_j(x, y) log_2 P_j(x, y) \tag{6}$$

GEnI [2] is extracted by computing entropy directly from GEI using (6), where $P_1(x, y)$ represent the value from GEI and $P_0(x, y) = 1 - P_1(x, y)$, as are shown in Fig. 1c. The GEnI contains dynamic body areas (e.g., leg, arms) which undergo consistent relative motion during a gait cycle will lead to high gait entropy value, whereas those areas that remain static (e.g., torso) would give rise to low values.

3.4 Frequency-domain gait entropy (EnDFT)

Both GEI and DFT include static (e.g., torso) and dynamic (e.g., leg, arms) components together. However, it was reported in [2] that they are vulnerable in the presence of significance change in appearance due to different cofactor. GEnI usually outperforms GEI, but it produces similar result to the DFT because the last two components of DFT represent the most dynamic nature of the gait.

We propose frequency-domain based entropy gait features here. The intensity value of the proposed EnDFT is computed using (6) from the DFT. Where $P_1(x, y)$ is the intensity value of DFT and $P_0(x, y) = 1 - P_1(x, y)$.

The main difference between GEnI and EnDFT gait feature is that GEnI is calculated from GEI whereas EnDFT is derived from DFT representation. The DFT representation of gait shows better result than GEI for its separated two dynamic higher frequency components. The one- and two-times frequency elements in the DFT hold only the uncertainty values of the gait. Therefore, the entropy based transformation of the DFT clearly separates the most uncertainty areas by adding one- and two- times components to the GEI. It is visible from Fig. 1d that proposed EnDFT gives more weights into dynamic areas and less near to zero into static areas by using all three components of the DFT. It is simple to generate EnDFT directly from DFT features just computing the entropy.

4 Effective part definition and selection

Based on the recognition accuracy of each row of DFT gait features, Rokanujjaman et al. [27] defined three effective parts and two less effective parts and preliminary results are reported. For part definition and selection the training subset of the OU-ISIR gait database, Treadmill dataset B [23] is used. The effectiveness of the proposed method is shown using the same database.

4.1 Part definition

The whole human body is divided into very small segments each of which is considered as a single row for part definition. We start from the bottom row and measure $rank - 1$ identification rate. Then each immediate upper single row is merged and calculated the recognition rate in each step until the top row is reached. The training subset of the OU-ISIR Gait Database, the Treadmill Dataset B is divided into gallery and probe subset for finding the recognition rate. Gallery subset contains only the standard clothing type and probe subset consists with other clothing types. The effect of cumulative row-wise recognition rate is shown in Fig. 2.

It is clear from the Fig. 2 that each row has either positive or negative effect in total recognition accuracy. From this observation, we can define the body parts based on the positive or negative contributions of the consecutives rows.

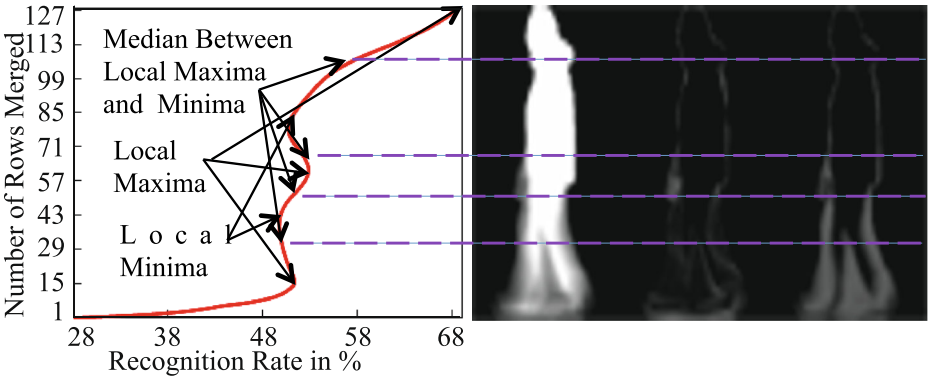


Fig. 2 Recognition rate for each row from bottom to top

First local minima and maxima are explored from the row-wise $rank - 1$ identification rate. The local minima corresponds to the less effective and maxima corresponds more effective areas of the human body. The body areas containing local maxima contributed the most in gait recognition while the body areas consisting of local minima have less contribution. Therefore, human body can be divided into parts with some consecutive rows containing local minima and maxima. In one way, the local minimum and maximum bound the area of a part. The part consists of consecutive rows with either positive or negative contributions for row-wise recognition. In this case, the body parts can be mixed up with static and dynamic area of the body that reduce the recognition accuracy. Another alternative is that the area of a part is bounded by the median between the local minimum and maximum. The part may consist of consecutive rows with positive or negative contributions for row-wise recognition. The body parts correspond to the static and dynamic area without combining them together. The median balances the distribution between minimum and maximum that can reduce the outlier effect for a part. We follow the later technique here.

We start the curve from top row (maximum here) until a local minimum is found. After getting one local minimum, we find out median between maximum and minimum and divide the body here. We then search for another local maximum and calculate the median of the first minimum and second maximum and divide the body. Similarly, we search for every pair of adjacent local maximum and minimum, and divides the body at their median. We repeat this process until reaching to the bottom row. If the last minimum is the bottom, there is no division of the body. Following the procedure, human body is divided into five parts as shown in Fig. 2.

4.2 Part selection

The body parts that include local minimum show negative effect in overall recognition rate and the parts that include local maximum have very good positive effect in overall recognition rate (more detail is discussed in the Section 6.2). Therefore, the parts that include local maximum are selected as effective parts and the parts that include local minimum are discarded as redundant parts empirically. Figure 3 shows the three effective parts $(EPi)\,\{i = 1, 2, 3\}$ and two less effective body parts $(LEPj)\,\{j = 1, 2\}$.

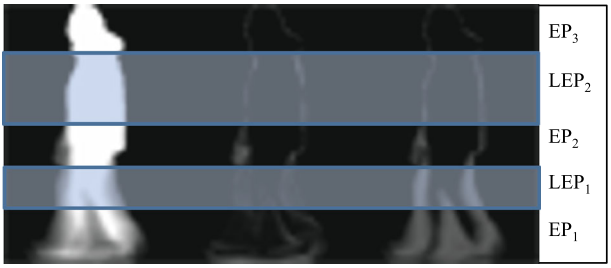


Fig. 3 Three effective parts (EP1, EP2 and EP3) and two less effective parts (LEP1 and LEP2)

5 Effective part-based features extraction and classification

From the five parts of the human body when two parts are discarded dimension of the data is automatically reduced. Principal component analysis (PCA) is applied to each effective part for further reduction of the dimension. The dimension reduced features are used for gait identification.

5.1 Effective part-based dimension reduced gait features

The dimension of the represented gait features is usually higher than training data. The statistical dimension reduced approach such as PCA, linear discriminant analysis (LDA) [4] only preserves the features, which contribute the most.

The part selection method (discussed in Section 4.2) defined two less effective body parts. These parts may change frequently due to different cofactors, in particular, some challenging cofactors such as clothing variations and carrying objects. Discarding these two less effective body parts, it is possible to reduce the dimension of the gait features as well as increase the recognition performance. The system can reduce 47 % dimension by discarding the two less effective body parts as redundant. Therefore, it can be a considerable technique for representing the gait features in lower dimensional space.

Each of these three effective parts is trained individually in the PCA subspace using the proposed EnDFT features to further reduce the dimension. The dimension-reduced gait features are used for part-based gait identification.

5.2 Effective part-based classification

Let a probe sequence P with m subsequences $P_r\,\{r = 1, .., m\}$ and a gallery sequence G with n subsequences $G_s\,\{s = 1, ..., n\}$. The matching measure for the subsequences is simply chosen as the Euclidean distance between P_r and G_s (let $d^{sub}(P_r, G_s)$).

First we compute the minimum distances for each of the probe subsequence Pr to a gallery sequence G is defined with i^{th} body part as:

$$d_i^{sub}(P_r, G) = \min_s \left[d_i^{sub}(P_r, G_s) \right] \tag{7}$$

Then, we compute the median of the minimum distances for each of the probe subsequence P_r as the distance between a probe P and a gallery G sequence is defined as:

$$D_i(P, G) = Median_r \left[d_i^{sub}(P_r, G) \right] \tag{8}$$

In part-based classification, we combined all the individual part distance into a single distance by summation for N_{parts}.

$$D(P, G) = \sum_{i=1}^{N_{parts}} D_i(P, G) \tag{9}$$

The final distance $D(P, G)$ is used for classification both for part-based and whole based methods.

6 Experimental result and discussion

This section shows experimental results using different datasets. The experimental results show the effectiveness of the effective and less effective body parts for human gait recognition using proposed EnDFT features.

6.1 Datasets

We have used two benchmarking gait datasets: the OU-ISIR Gait Database, the treadmill dataset B [23] and CASIA Gait Database, dataset B [35] to evaluate the performance of the proposed approach against the clothing and carrying object cofactors.

The OU-ISIR Gait Database, the Treadmill Dataset B This dataset was chosen due to its largest clothing variations. Considering one of the most challenging cofactors: clothing, recent work [23] created the OU-ISIR Gait Database, the Treadmill Dataset B with large clothing variations. It includes 68 subjects with at most 32 combinations of different types of clothing such as skirt, raincoat, down jacket, long coat, hat, parker, muffler, short pants, casual wears, regular pants, half shirt, full shirt etc. The whole dataset is divided into three subsets: training set, gallery set and probe set. In training set there are 446 sequences of 20 subjects (10 males and 10 females) with the range of 15 to 28 different combinations of clothing. The testing set (gallery and probe sets) consists of other sequences of the rest 48 subjects excluding the 20 training subjects. Gallery set containing only standard clothing type, i.e., regular pant and full shirt of 48 subjects. Probe set containing 856 sequences of these 48 subjects considering all types of different clothing combinations excluding the standard one type.

CASIA Gait Database, Dataset B This dataset was chosen due to its subject diversity with multiple sequences with clothing and carrying object cofactors. More specifically, this dataset comprises three cofactors normal walking sequences, carrying objects (i.e., carrying a bag) and only one clothing type (i.e., wear a bulky coat). There are total 124 subjects and each subject contains 10 walking sequences. Based on the three cofactors the whole dataset is divided into three subsets. CASIASetA consists of six normal walking sequences where the subject does not carry a bag or wear a bulky coat. CASIASetB consists of two carrying-bag sequences and set CASIASetC consists of two wearing-coat sequences. The gallery set is constructed by taking the first four sequences of each subject in CASIASetA (CASIASetA1). The probe set is the rest two sequences in CASIASetA (CASIASetA2), two sequences in CASIASetB and two sequences in CASIASetC. The gallery set is used as training set for CASIA Gait Database, Dataset B.

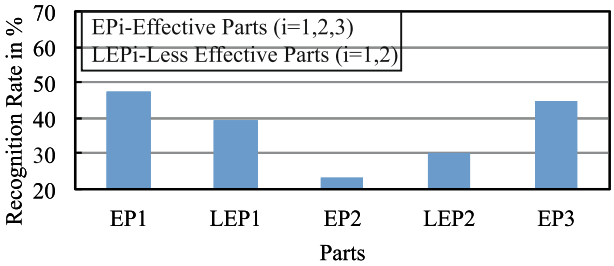


Fig. 4 Part-wise recognition rate

Although we notice that the USF HumanID Gait Challenge Dataset [28] is also one of well-known benchmarking gait databases, we did not include it in our experiments due to smaller clothing variations than those with the OU-ISIR Gait Database, the Treadmill Dataset B, and the smaller number of sequences per subject per cofactor than that of CASIA Gait Database, Dataset B.

6.2 Experimental validation of three effective parts

The human body is divided into five parts: three effective parts $(EPi)\{i = 1, 2, 3\}$ and two less effective parts $(LEPj)\{j = 1, 2\}$. Figure 4 shows the recognition rate for each individual part separately. The consecutive merging or discarding effect of the effective and less effective parts is shown in Fig. 5. It is observed from Fig. 5 that when each of the three effective parts are combined then the recognition rate are increased dramatically and when each of the two less effective parts are combined with the other effective parts cumulatively then the recognition rate are decreased. Although the recognition rates of some effective parts are lower than the less effective parts, the combined performance of effective part is better. The reason is that the less effective parts recognize the similar subjects where the effective parts can recognize different individual with cofactors.

6.3 Effective parts on different gait representations

To show the further effectiveness of the proposed parts definition, we perform experiment for different gait representation techniques separately on both the OU-ISIR Gait

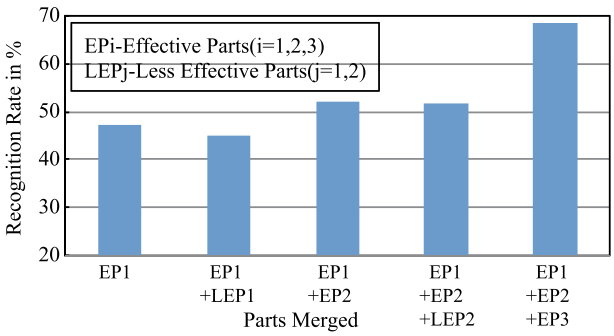


Fig. 5 Combining effect of the effective and less effective parts in overall recognition

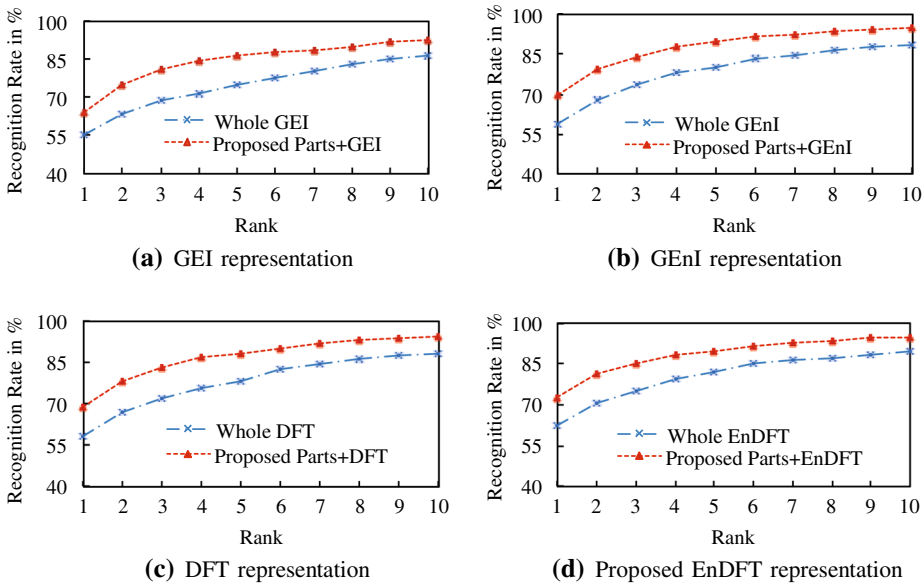


Fig. 6 Comparison of the proposed effective part-based with whole-based methods using different gait representations (i.e., GEI, DFT, GEnI and proposed EnDFT) in the OU-ISIR Gait Database, the Treadmill Dataset B

Database, the Treadmill Dataset B and CASIA Gait Database, Dataset B. The Cumulative Matching Curve (CMC) of Fig. 6 shows the comparison of the whole-based and the effective part-based recognition rate for different gait representation techniques using the OU-ISIR Gait Database, the Treadmill Dataset B. On the other hand, Fig. 7 shows the CMC curves comparing the whole-based and the effective part-based recognition rate for different gait representation techniques using CASIA Gait Database, Dataset B. Table I shows the $rank - 1$ recognition rate for the whole-based and the effective part-based methods using all representations. It also shows the reported result of the popular methods [3, 12, 35] using the CASIA Gait Database, Dataset B. It is obvious that the proposed effective part-based method produces always better results than other whole-based methods in all of the reported gait representation techniques for the OU-ISIR Gait Database, the Treadmill Dataset B and the whole CASIA Gait Database, Dataset B datasets except for the subset of CASIA dataset CASIASet2 (Table 1).

6.4 Effect of frequency domain gait entropy features

The proposed frequency domain gait entropy features (EnDFT) are compared with three others gait representations GEI, DFT, and GEnI in both the OU-ISIR Gait Database, the Treadmill Dataset B and CASIA Gait Database, Dataset B (CASIASetA2, CASIASetB, CASIASetC) datasets (Fig. 8). The EnDFT gait features show much better performance in all datasets except CASIAsetA2. The EnDFT highlights the most discriminative dynamic areas while minimizing the effect of the static areas. It was also reported in [2] that static areas can be over-fitted when the appearance is significantly changed by clothing and carrying cofactors.

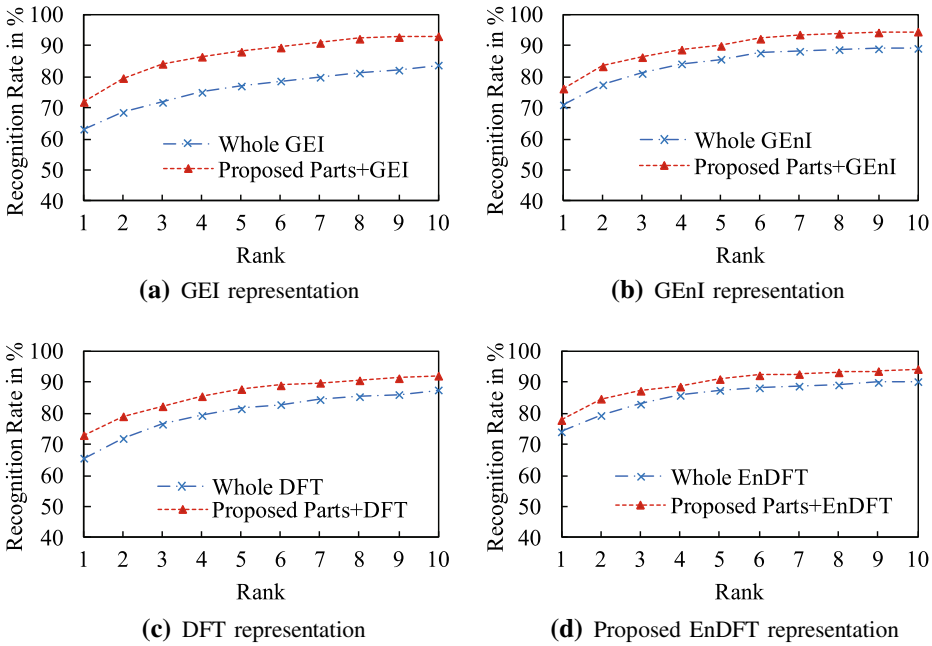


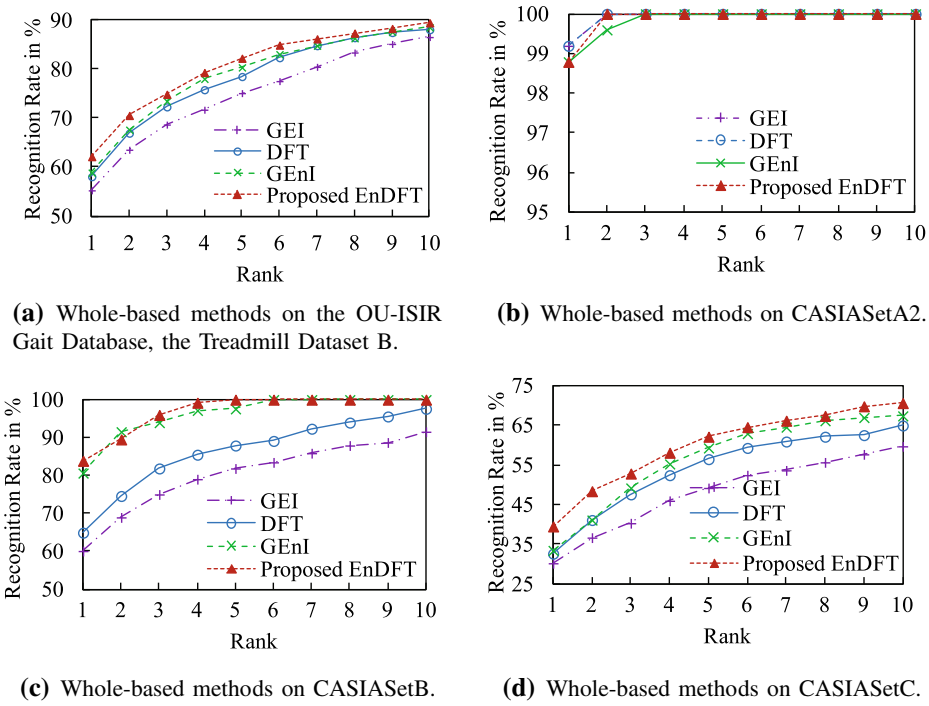
Fig. 7 Comparison of proposed effective part-based with whole based methods using the different gait representations (i.e., GEI, DFT, GEnI and Proposed EnDFT) in CASIA Gait Database, Dataset B

6.5 Effective parts with EnDFT feature on clothing complexity

To find out the complexity of individual clothing of the OU-ISIR Gait Database, the Treadmill Dataset B, the training set is divided into two subsets: gallery with standard clothing and probe contains the rest clothing types. We compute the recognition rate for all clothing types and arrange them in descending order as shown in Fig. 9. Figure 10 shows the sample images according the sorted clothing types with gallery.

Table 1 Comparison of proposed effective part-based with whole based methods using different gait representation

Methods / Datasets	OU-ISIR	CASIA Set A2	CASIA Set B	CASIA Set C
Yu et al. [35] (%)	–	97.6	52.0	32.7
Han et al. [12] (%)	–	99.4	60.2	30.0
Bashir et al. [3] (%)	–	100.0	78.3	44.4
Whole GEI (%)	55.25	99.04	60.08	30.24
Whole DFT (%)	58.06	99.04	64.92	32.66
Whole GEnI (%)	58.87	98.56	80.64	33.47
Whole proposed EnDFT (%)	62.15	98.56	83.87	39.51
Proposed Parts+GEI (%)	64.01	98.56	75.00	41.93
Proposed Parts+DFT (%)	68.69	96.65	79.03	42.74
Proposed Parts+GEnI (%)	69.62	97.61	83.46	47.17
Proposed Parts+Proposed EnDFT (%)	72.90	97.61	83.87	51.61



(a) Whole-based methods on the OU-ISIR Gait Database, the Treadmill Dataset B.

(b) Whole-based methods on CASIASetA2.

(c) Whole-based methods on CASIASetB.

(d) Whole-based methods on CASIASetC.

Fig. 8 Whole-based methods comparison using proposed EnDFT representation with other existing representations (GEI, GEnI and DFT) in both datasets (the OU-ISIR Gait Database, the Treadmill Dataset B and CASIA Gait Database, Dataset B)

Clothing types that are similar with gallery gives better recognition rate. On the other hand, recognition rate decreases for dissimilar clothing types. It is observed in Figs. 9 and 10 that the recognition rate decreases with increasing the clothing complexity.

For analyzing the clothing complexity and the effect of the proposed system, we make three groups of all the clothing types using k-means clustering techniques. The training probe subset is used here. Table 2 shows the three clusters with clothing Ids and cluster 1 to cluster 3 are arranged from simple to complex clothing types. To evaluate the performance, we compare the proposed system with the system using whole DFT and EnDFT features for the test dataset. Figure 11 shows the comparison results.

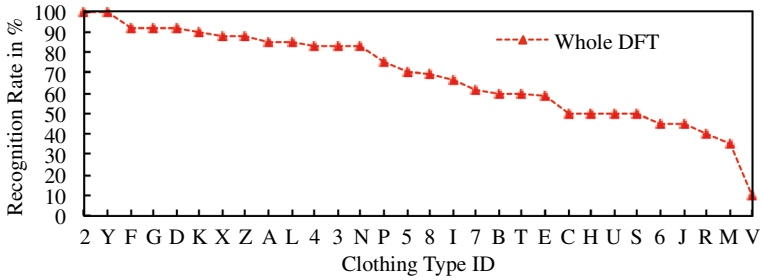


Fig. 9 Sorted clothing types according to recognition rate

Fig. 10 Sample clothing images [13] of the OU-ISIR Gait Database, the Treadmill Dataset B according to sorted ID

Table 2 Clothing clusters

Cluster ID	Clothing IDs	Percentages of clothing types
Cluster 1	Y,X,Z	10.00 %
Cluster 2	2,F,G,D,K,A,L,4,3,N,P, 5,8,I,7,T,E,U,S,6,J,R	73.33 %
Cluster 3	H,B,M,C,V	16.67 %

For relatively simple clothing types, whole-based methods is slightly better for recognition than the proposed method. However, for complex clothing types in cluster 2 and cluster 3, the performance of the proposed method is much better than whole-based methods. It is noticeable that cluster 1 contains only 10 % of the clothing types and the performance of the proposed part-based EnDFT method is increasing with the increases of clothing complexity. Thus, it is validated that the proposed features can represent the gait with the most discrimination capability and the effective parts selection enhance the recognition rate with reduced data. It is also supported by the result shown in Table 1 that the proposed system outperforms in clothing and carrying conditions for CASIA Gait Database, Dataset B.

6.6 Comparisons with other methods

The performance of the proposed effective parts with EnDFT features based method is compared with four widely used whole-based methods [2, 12, 20, 22] and one part-based methods [13]. The whole-based methods [20] used GEI and [22] used frequency domain FFT gait features that are dimension reduced by the PCA. The LDA based methods [12] and [2] used GEI and GEnI gait features respectively. In the LDA based methods, we have used the training set for both datasets in the training stage where first the dimensions are reduced by PCA, and then LDA is applied. The part-based method [13] defined eight parts: four consecutive parts and four overlapping parts based on anatomical statistics on DFT gait features. The performance is evaluated using these eight parts without adaptive weighting. Figure 12a shows comparison experiment on the OU-ISIR Gait Database, the Treadmill Dataset B and Fig. 12b on CASIA Gait Database, Dataset B using CMC curve.

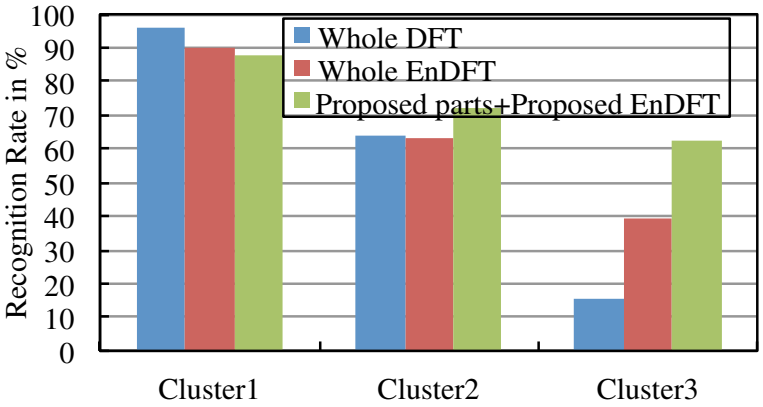
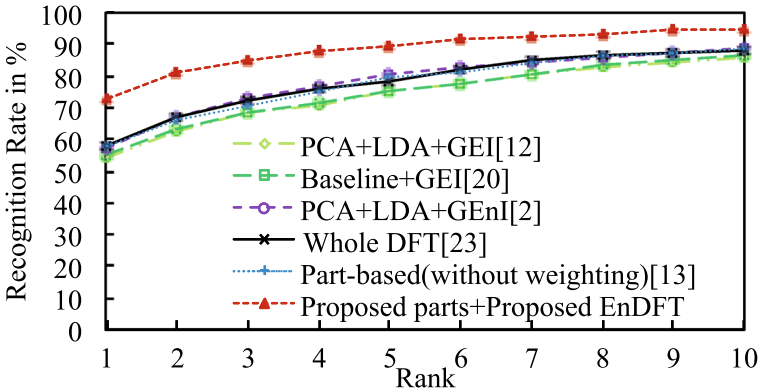
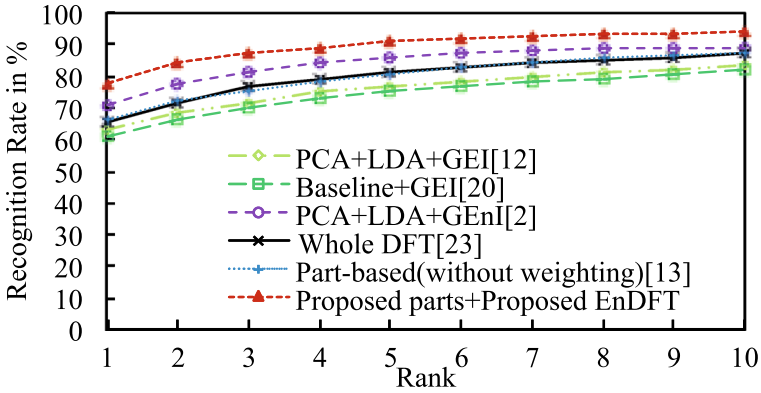


Fig. 11 Comparison of cluster-wise recognition rate



(a) Comparison with other methods on the OU-ISIR Gait Database, the Treadmill Dataset B.



(b) Comparison with other method on total CASIA Gait Database, Dataset B.

Fig. 12 Algorithms comparison on the OU-ISIR Gait Database, the Treadmill Dataset B and CASIA Gait Database, Dataset B

6.7 Discussion

The main contribution is to define the effective body parts definition with proposed frequency domain-based entropy gait features (EnDFT). The comparison results are shown in Figs. 6, 7 and 8. The proposed method is always shows better performance for both the OU-ISIR Gait Database, the Treadmill Dataset B and CASIA Gait Database, Dataset B datasets. The experimental results are summarized in Table 1. The results clearly show that the proposed EnDFT based gait features produced better performance in comparison with others reported representation techniques. The proposed effective parts definition show much better result than whole-based representation on all of the gait representation techniques especially for the new proposed gait representation techniques (EnDFT).

The proposed effective parts definition is very much effective in the presence of significant change of appearance due to challenging clothing cofactors on the both datasets. One interesting observation is that discarding the two less effective body parts i.e., using the

three effective body parts with the EnDFT gait features is still give the same result as for the whole based representation in presence of carrying-bag conditions for CASIASetB dataset. Another observation is that in case of the OU-ISIR Gait Database, the Treadmill Dataset B (Fig. 11) and CASIASetA2 dataset (Table 1) where normal clothing are used the whole-based representation gives slightly better result than effective part-based method although the result is comparable. However in real application, we cannot always expect uniform normal clothing. The performance of the proposed part-based EnDFT method increases with the increases of the clothing complexity (Fig. 11).

7 Conclusion

We propose the effective part-based gait identification using frequency domain-based gait entropy features (EnDFT). To find out the effective body parts, we have proposed a more robust technique by dividing the whole body into small segments where each segment is a single row in this paper. Based on positive and negative effect of each segment, three effective parts and two less effective parts are defined. We have also investigate different gait representation techniques and the proposed a new frequency domain-based gait entropy features EnDFT. The proposed method outperforms other classical gait recognition algorithms and representation techniques in both the OU-ISIR Gait Database, the Treadmill Dataset B and CASIA Gait Database, Dataset B datasets.

Since our effective part selection method is applicable to any types of the gait features which are represented as a set of point statistics (e.g., gait flow image [16], chrono-gait image [33], Masked-GEI [3]) without any changes, we will further investigation on the combination of our effective part selection method and state-of-the-art gait features in future work. Moreover, adaptive fusion of all the parts without just discarding the less effective parts will be another future extension of this work.

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