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Speed Invariant Gait Identification using Frequency Domain Feature

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Abstract

Changes in walking speeds is one of the most challenging covariates in gait identification. Walking speed changes is accountable to significantly alter walking patterns of an individual. This covariate is also responsible for the intra-class variations and for that the training dataset fails to cope with. This covariate may affect some parts of human gait and keep other parts untouched. To address this issue parts definition and selection is carried out based on GEI feature to show which parts are contributing more and which parts are contributing less in gait identification under different speed changes. After having a suitable combination of different parts of gait, frequency domain feature is extracted from that part and used in gait identification. We evaluate and analyse the performance of our proposed method and other existing methods on a publicly available OU-ISIR Treadmill Dataset A. In this paper, we focus on the walking speed and deal with cross speed gait identification and achieve better identification rate.

Keywords: Gait identification, parts definition, parts selection, speed invariant, intra-class variation

INTRODUCTION

Gait identification means endorsing a person by his or her style of walking. However a person's gait is affected or altered by cofactors including shoe type, heel height, clothing, walking speed, illness, injury, emotional state, environment, and so forth. Human gait identification has several unique characteristics that other biometric lack. (i) Gait identification can be done at low image resolution [1, 2]. (ii) Gait can be captured far away from the person and without the understanding of a person. (iii) Gait as insensible behaviour is difficult to be spoofed. These favourable characteristics have vital significance. Considering the above characteristics, applications of the gait identification are ranging from video-based wide-area observation [3, 4] to criminal investigation.

This paper is an extension of our previous paper [5]. In this paper, the affected body parts due to walking speed changes are discarded and unaffected body parts are processed for gait identification. The parts definition and selection is carried out on the basis of Gait Energy Image (GEI). Then gait identification is done on the basis of DFT. The main contribution of our proposed approach is to define the body parts and create a look up table to select the most effective parts for the different walking speed combinations of the gait and discard the redundant parts to minimize the intra-class variation and overcome the difficulties arises in speed changes cofactor conditions.

The rest of the paper is organized as follows. Introduction is our first Section. Section two is devoted to the review of the some existing

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approaches for gait identification. Section three contains the gait feature representation and walking speed estimation. In Section four, matching measure is described. Section five is devoted to part definition and selection. In section six, experiments are demonstrated. Result and discussion are presented in Section seven. Finally concluding remarks are given in the last section.

REVIEW OF THE EXISTING APPROACHES

Gait identification approaches can be divided into two broad categories: (i) Model-based and (ii) Model-free or feature-based approaches [6, 7, 8].

The model-based approaches model human body and extract features from the model. In [9], a human body is modelled and kinetics of leg motion is extracted as a gait feature using Fourier analysis. An articulated body model is designed and static shape parameters, gait period [10] and joint angles [4] are extracted as a feature. In [11] a model of human body as a 2D stick model is proposed on the basis of human anatomy [12]. On the other hand, a marionette mass-spring model for 3D gait identification is proposed as a more mechanical model [13]. This has 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 [14] reports that high quality gait image sequences are required to achieve a high accuracy.

In contrast, model-free or feature-based approaches did not model human body. It represents the human gait as a whole without knowing the underlying structure of the human body. The first model-free gait representation approach named GEI was introduced representing features in the video as a single image [15]. In [5], GEI feature based method for parts definition and selection is proposed to solve the speed invariant gait identification problem by discarding the affected body parts. Model-free approaches [16, 17] are comparatively insensitive to the quality of gait silhouettes and have the benefit of less computational costs and complexity compared to model-based approaches. Therefore, model-free feature representation is popular. However, significant change in appearance due to the effect of different cofactors makes the model free gait recognition task much more complicated. These cofactors include walking speed, clothing conditions, carrying objects, lengthy time interval, frame rate, viewing angles and surfaces. These cofactors may affect some parts of whole gait where other parts that are useful for gait identification remain unchanged.

Usually, for the whole-based methods, large numbers of training subjects are required to address the variation of full-body gait features. On the other hand few numbers of training subjects are required for part-based gait identification due to its low dimensionality.

In case of different part-based gait representation techniques there is still a major challenge to define the effective body components that influence the gait identification under the effect of different cofactors. Two considerations could assist to lift the identification accuracy in case of different cofactors (i) Gait features should contain the most discriminating information and (ii) More affected and less affected body parts should be taken into account for selecting the appropriate body parts. In [2, 18, 19, 20], the body parts are predefined. Therefore, predefined parts based approach cannot define and select the most effective parts and the less effective parts considering the influences of different cofactors. On the other hand a part-based approach is proposed in [21, 22] where the most effective body parts and less effective parts are defined on the basis of the experimental result.

It should be noted that walking speed variation is the most challenging cofactors in gait identification due to the dynamic parts of the gait affected with speed changes. There are two walking speed invariant gait identification methods [23]. The first method is based on the transformation of features from one speed to other speed before classification. A method of gait silhouette transformation from one speed to another speed is developed by factorization based speed transformation model using SVD [24]. In [25], a stride normalization procedure is developed to model walking gaits across different walking speed cofactors. The second method is based on extracting speed invariant gait feature from gait template to minimize intra-class variation. Procrustes Shape Analysis (PSA) descriptors based method [23, 26] was developed to grip large changes in walking speed. Higher-order derivative Shape Configuration (HSC) was used to extract speed invariant gait features from PSA descriptors. HSC was extended based on Differential Composition Model (DCM) [23] to compute and assign weights to different body parts. DCM shows substantial performance improvements than HSC in case of large speed changes. In [1], Head and Torso Image (HTI) was proposed by discarding the mostly affected legs part due to speed changes. A classifier ensemble framework based on Random Subspace Method (RSM) was proposed in [27] to overcome the cross speed gait identification problem. It was claimed in [27] that RSM framework can perfectly resolve the speed changes problem. The experiment was executed ten times and calculated the mean CCR for the randomness of the method. The method achieved better performance but due to the randomness and time complexity this method could not guarantee the best accuracy [28].

GAIT FEATURE REPRESENTATION AND WALKING SPEED ESTIMATION

The OU-ISIR gait dataset was captured at 60 frames per second and 640 × 480 pixels per frame. Silhouettes are extracted from each frame of a video sequence by subtracting background or redundant pars. Then each background-subtracted silhouette found from a frame is registered to obtain the spatial-temporal gait silhouette volume (GSV) [3]. 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 cycle G_{cycle}, where G_{cycle}=3 in our experiment. In most of the feature-based approaches, features are extracted from silhouettes.

Feature Representation

The average of silhouette images calculated over a complete gait cycle is called Gait Energy Image (GEI) [29]. In model-free approaches [21, 22, 29, 15], GEI is used as a feature. In our proposed method, GEI is used for part definition and selection. In GEI, the static (head and body) and dynamic areas (swings of legs and arms) are spotted on the basis of intensity. Given a sequence of pre-processed binary gait silhouette images $B(x, y, n)$, the grayscale GEI is defined as,

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

where, *x* and *y* denote the pixel coordinate in the 2D image, *N* is the total number of frames in a gait cycle and *n* is the frame number. Some GEIs are shown in Figure 1.

Figure 1. Gait Energy Image (GEI).

Discrete Fourier Transform (DFT)

Another gait feature based on DFT is calculated from the silhouette images over a complete gait cycle. This feature is not used in part definition and selection phase. However, this feature is used in our experiment phase. By applying the DFT over the images in a gait cycle, an amplitude spectrum of the GSV is calculated [3]. DFT and amplitude spectra is calculated through the following equation

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

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

where, x and y denote the pixel coordinate in the 2D image, N is the total number of frames in a gait cycle and n is the frame number, ω_0 is the base angular frequency for a gait cycle and k is the frequency component. Only first three frequency components are taken into account for DFT calculation. Other frequency components representing noises are discarded. Among the three frequency components, first component is equivalent to GEI, second component represents the asymmetry of the left and right motion and the third component represents the symmetry. In addition to DFT, Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) are used in our experiment.

Gait Speed Estimation

Usually, walking speed is measured in a unit of km/h. Given walking speed of each gait cycle of training dataset, walking speed of each gait cycle of test dataset is estimated and classified. Each gait cycle contains a number of frames on the basis of walking speeds. Table 1 shows the number of frames per gait cycle estimated under the various walking speeds based on training dataset of the OU-ISIR gait dataset A. It is evident in Table 1 that lower frame rate correspond to the higher walking speed and vice versa.

Table 1. Frame estimation for different speeds.

Speed (km/h)	Average no. of Frames per gait cycle
2	88
3	75
4	69
5	63
6	59
7	55

MATCHING MEASURE

Usually distance between two feature vectors is measured by Euclidean distance. Euclidean distances are calculated between feature vectors of each gallery and each probe for the subsequences with G_{cycle} frames. This is a brute-force approach. There are three different methods for matching measure. First method calculates the mean value of the minimum distances of the subsequences. Second method calculates the median value of the minimum distances. Third method calculates the minimum value of the minimum distances. Last one is used in our experiment.

Let $\left\{x_j^p\right\}$ (j=1 to G_{cycle}) and $\left\{x_k^g\right\}$(k=1 to G_{cycle}) be the subsequences for the probe x^p and gallery x^g respectively. The Euclidean distance denoted by $d^{subs}\left(x^p, x^g\right)$ is the matching measure between the subsequences of a probe and a gallery. The minimum value of the minimum distances of the combinations of subsequences of each probe and gallery is defined as

$$d^{\min}(x^p, x^g) = \min_j [\min_k \{d^{subs}(x_j^p, x_k^g)\}] \tag{4}$$

PARTS DEFINITION AND SELECTION

The main contribution of the proposed system is to define the parts and select the most effective parts for different speed combinations of the GSV and discard the redundant part to overcome the difficulties arises in speed covariate conditions. For dividing the body horizontally into different parts, we study the contribution of different segments of GEI in terms of identification rate of the training dataset. The smallest segment in this case is a bottom most row. Next segment consists of two most bottom rows and so on.

Parts Definition

How a body is portioned into unequal parts is described in this section. We measure the recognition rate row wise starting from the bottom row of GEI feature and then merging a next upper single row in each step.

The number of rows in each segment along with their identification rate is plotted in Figure 2. A curve is found in the Figure 2. The curve is plotted from top to bottom. Small segments along with their identification rates are plotted first. Then next larger segments with their identification rates are plotted and so on until the bottom of the curve. It is clear that sometimes a row in a segment has positive effect and sometimes has negative effect in terms of identification rate. Form these findings; we can define the body parts based on the positive or negative contributions of the consecutive rows.

In the Figure 2, there are three local maxima's and three local minima's in the curve. Starting from the top of the curve a pair of consecutive local maxima-local minima or local minima-local maxima is spotted and mean is calculated between them to divide the body in that location. Following the procedure, human body is divided into six unequal parts as in Figure 2. If the last minima is in the bottom part of the curve, it ends the partition process.

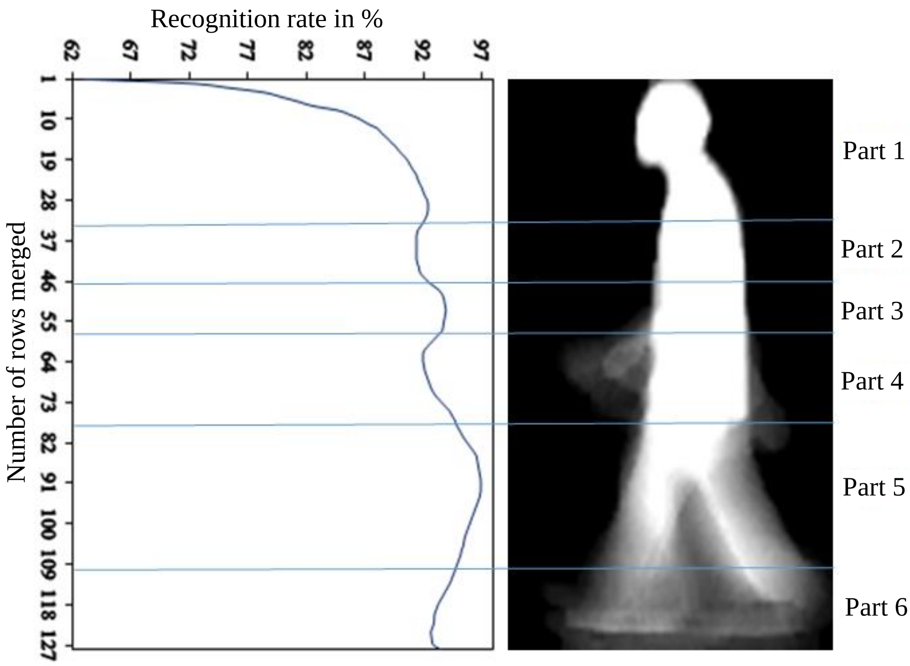

Figure 2. Parts definition based on local maxima and local minima [5].

Part Selection

The body parts are divided into six unequal parts based on the positive or negative contributions of the consecutive rows. The recognition rate is calculated in Table 2 for cross speed gait by combining different body parts of training dataset. It is observed that for some combinations the recognition rate is high and for some combinations the recognition rate is low. The best combinations with their recognition rate are shown in Table 2. It is also observed that for same gallery probe combinations more than one combinations of body parts giving the same recognition rate. Also for cross speed different combinations of body parts are effective. The body parts which are selected from Table 2 for cross speed gait identification based on training dataset is shown in Table 3. So only the common body parts as effective are selected for our proposed cross speed gait identification task which is shown in Table 3.

Table 2. Different combination of parts with cross speed identification rate in %.

Probe Gallery	2km/h	3 km/h	4 km/h	5 km/h	6 km/h	7 km/h
2 km/h	1, 2, 3, 4, 5, 6 (100%) 1, 2, 3 (100%)	1, 2, 3, 5, 6 (100%) 1, 2 (100%)	1, 2, 3 (94.4%) 1, 2 (94.4%)	1 (94.4%)	1 (83.3%)	1 (72.2%)
3 km/h	1, 2, 3, 5 (100%) 1, 2, 3 (100%) 1, 2 (100%)	1, 2, 3, 4, 5, 6 (100%) 1, 2 (100%)	1, 2, 3, 4, 5, 6 (94.4%) 1, 2, 3 (94.4%) 1, 3, 6 (94.4%) 1, 2 (94.4%)	1, 2, 5 (83.3%) 1, 2 (83.3%)	1 (83.3%)	1 (72.2%)
4 km/h	1, 2, 3, 6 (94.4%) 1, 2, 3 (94.4%) 1, 2 (94.4%)	1, 3, 6 (83.3%) 1, 3 (83.3%)	1, 3, 4, 5, 6 (94.4%) 1, 3, 4, 5 (94.4%) 1, 3, 4 (94.4%) 1, 3 (94.4%)	1, 2, 3 (94.4%)	1 (77.8%)	1 (77.8)
5 km/h	1, 2 (88.9%)	1, 2, 6 (83.3%) 1, 2 (83.3%)	1, 2, 3 (100%)	1, 3, 4, 5, 6 (100%) 1, 3, 4, 5 (100%) 1, 3, 4 (100%)	1 (88.9%) 1, 6 (88.9%)	1 (88.9%)
6 km/h	1 (88.9%)	1, 2 (94.4%)	1, 2 (72.2%) 1 (72.2%)	1 (100%)	1, 2, 3, 4, 5, 6 (100%) 1, 2, 3, 4, 5 (100%) 1, 2, 3, 4 (100%)	1, 6 (94.4%) 1 (94.4%)
7 km/h	1 (72.2%)	1, 2, 6 (55.6%) 1, 2 (55.6%) 1 (55.6%)	1 (77.8%)	1 (88.9%)	1, 3, 4 (94.4%) 1, 3 (94.4%) 1, 4 (94.4%) 1(94.4%)	1, 3, 4 (94.4%) 1, 3 (94.4%) 1, 4 (94.4%) 1 (94.4%)

Table 3. Parts selection table for cross speed gait identification.

Probe Gallery	2 km/h	3 km/h	4 km/h	5 km/h	6 km/h	7 km/h
2 km/h	1, 2, 3, 4, 5, 6	1, 2, 3, 5	1, 2, 3	1	1	1
3 km/h	1, 2, 3, 5	1, 2, 3, 4, 5, 6	1, 3, 6	1, 2	1	1
4 km/h	1, 2, 3	1, 3, 6	1, 3, 4, 5, 6	1, 2, 3	1	1
5 km/h	1	1, 2	1, 2, 3	1, 3, 4, 5, 6	1	1
6 km/h	1	1	1	1	1, 2, 3, 4, 5, 6	1
7 km/h	1	1	1	1	1	1, 3, 4

EXPERIMENTS

In our experiments, most challenging walking speed variant gait dataset is used to evaluate the performance of the proposed part-based method. For part definition and selection, OU-ISIR Treadmill Gait Dataset A [30, 31] which includes a large range of walking speed is used. This dataset consists of gait silhouette sequences of 34 subjects of both genders (26 males and 8 females). Side view of the subjects with speed variations from 2 km/h to 7 km/h at 1 km/h interval was considered for developing the dataset. This dataset enables us to evaluate not only speed invariant gait identification algorithms but also view and clothing invariant gait identification algorithms. Moreover, it enables us to perform gait-based gender classification and age group classification. In our experiment 9 subjects are considered in training phase and 25 subjects are considered in testing phase. These 9 subjects belong to the 108 sequences with different walking speeds. On the other hand 25 subjects belong to the 300 sequences with different walking speeds. Two video sequences were recorded for each of the 34 subjects with each speed. The dataset used in training phase is not used in testing phase. Gait identification findings are illustrated in Table 4. At rank-1, a noticeable identification rate is found.

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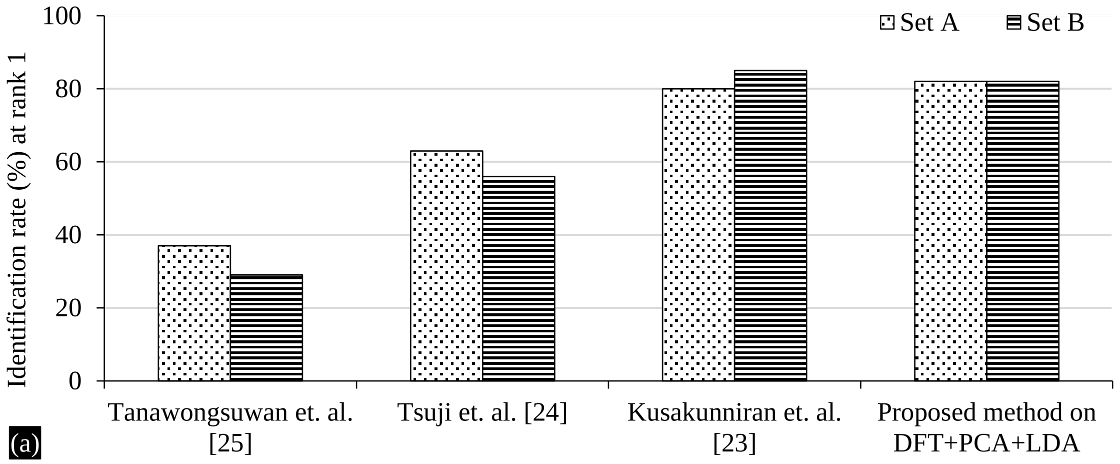
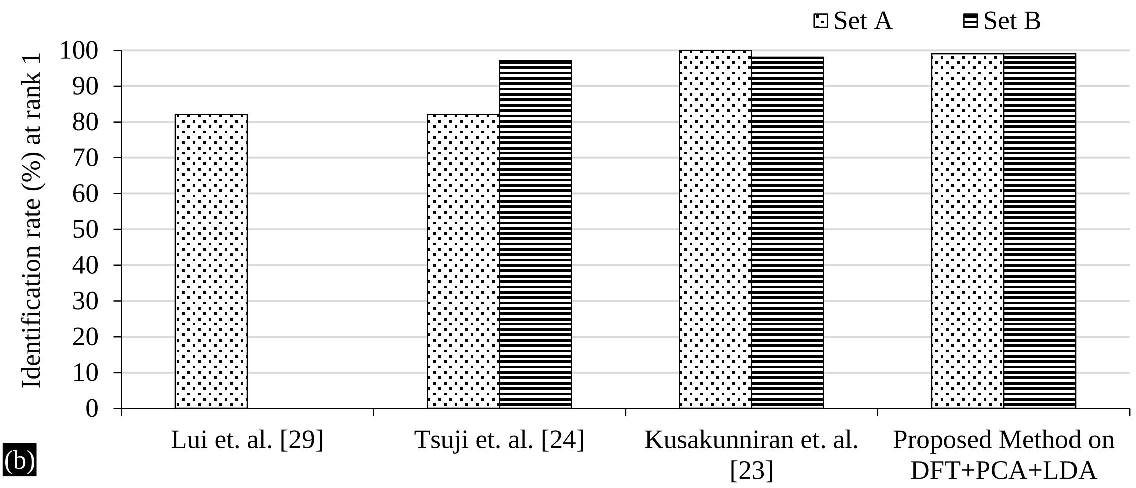
RESULT AND DISCUSSION

The cross gait identification rate at rank-1 is shown in Table 4 for our proposed method. On the other hand, the cross gait identification rate without DCM [23] is presented in Table 5. Our proposed method, identification rate ranges from 74% to 100%. However, identification rate without DCM ranges from 56% to 100%. It is clear from Tables 4 and 5 that our proposed method acts more effectively.

Our proposed method is evaluated with the existing methods proposed by Kusakunniranet. al. [23], Tanwongsuwan et. al. [25], Tsuji et. al. [24] and Liu et. al. [29] as shown in Figure 3(a) and Figure 3(b). The experiments are carried out on the same OU-ISIR gait dataset and under the similar covariate conditions for an impartial evaluation. The dataset is divided into large speed changes and small speed changes. Some samples from large speed changes are taken for set A as the gallery and some samples from large speed changes for set A as the probe. Samples are reversed in case of set B. Similarly samples from small speed changes are taken for set A and set B. According to the Figure 3(a), our proposed method average recognition rate for set A and set B (between 2 km/h and 6 km/h) is higher than others. However, the method proposed by Kusakunniran et. al. [23] achieved little bit higher recognition rate only for set B. In the Figure 3(b), very close identification rates are found for set B (between 3 km/h and 4 km/h) calculated by Tsuji et. al. [24], Kusakunniran et. al. [23] and our proposed method. This Figure also shows that average identification rate of our method is better than others. Moreover, in all cases our method is very much consistent than other methods.



(a)



(b)

Figure 3. (a) Comparison with other methods with large speed changes, (b) Comparison with other methods with small speed changes.

Table 4. Cross gait identification rate of the proposed method (%).

Probe Gallery	2 km/h	3 km/h	4 km/h	5 km/h	6 km/h	7 km/h
2 km/h	100	98	98	90	82	74
3 km/h	100	100	98	92	94	84
4 km/h	80	98	100	96	94	84
5 km/h	88	96	94	100	100	98
6 km/h	74	82	94	96	98	90
7 km/h	80	84	84	90	98	100

Table 5. Cross gait identification rate without DCM method (%) [23].

Probe Gallery	2 km/h	3 km/h	4 km/h	5 km/h	6 km/h	7 km/h
2 km/h	100	96	84	72	72	72
3 km/h	100	100	96	80	76	60
4 km/h	76	96	96	92	92	80
5 km/h	76	76	96	96	100	96
6 km/h	64	68	80	96	100	96
7 km/h	56	68	80	96	100	100

CONCLUSION

In this paper a method is proposed for human gait part definition and selection on the basis of GEI to cope with the intra-class variation caused due to large changes of walking speed. Based on our part definition and selection method a statistically reliable performance comparison of cross speed gait identification is carried out by various approaches. We confirmed that our method is potential, consistent and effective for gait identification. However, according to Tables 4 and 5, it should be noted that there is a correspondence between the higher identification rate and the small speed changes and vice versa. Addressing this issue new feature extraction methods could be proposed in the future work.

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