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Human Identification by Gait Using Corner Points

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***Abstract*—Recently human gait has become a promising and very important biometric for identification. Current research on gait recognition is usually based on an average gait image or a silhouette sequence, or a motion structure model. In this paper, the information about gait is obtained from the disparity on time and space of the different parts of the silhouette. This paper proposes a gait recognition method using edge detection, identification of corner points from edges, and selection of control points out of those corner points. Here, the images of moving human figures are subtracted from background by simple background modeling technique to obtain binary silhouettes. A gait signature of a person is taken as silhouette images of a complete gait cycle. A complete gait cycle is then divided into different frames in such a way that the information of the person's gait style can be represented fully. One given unknown gait cycle is compared with stored gait cycles in terms of a cyclic distances between control points of an image of input gait cycle with that of corresponding image of the stored gait cycle. Experimental results show that our method is encouraging in terms of recognition accuracy.**

***Index Terms*—Gait recognition, silhouettes, Edge Detection, corner detection, control points**

I. INTRODUCTION

Gait [1] is a behavioral biometric that measures the way people walk. The demand for automatic human identification system [2][3][4] is robustly escalating in many important applications, particularly at a distance. It has gained an immense interest for its uses in many security-sensitive environments such as banks, military, parks and airports. Biometrics is a powerful tool for reliable human identification. It makes use of human physiology or behavioral characteristics such as face, iris and fingerprints for recognition. However, these biometrics methodologies are either informative or limited to many environments. For example, most face recognition techniques are able to recognize only frontal or side faces or with some specified angle of turn or inclination, but if the face is not shown or only the back side of head is shown then it is of no use, other biometrics such as fingerprint and iris are no longer applicable when the person suddenly appear in the surveillance. Therefore, new biometric recognition methods are strongly required in many surveillance applications, particularly recognition at a distance. Compared with the first generation biometrics, such as face, fingerprints and iris, which are widely applied in some commercial and static applications, currently, gait is the only biometric at a distance, can be used when other biometrics are either obscured or at too low a resolution to be perceived till now, though it is also affected by some factors such as drunkenness, obesity, pregnancy and injuries involving joints. So to recognize an individual's walking characteristics, gait recognition includes visual cue extraction as well as classification. However, major issue here is the extraction and representation of the gait features in an efficient manner. Another motivation is that video footage of suspects can be made readily available, as surveillance cameras are relatively low cost and can be installed in most buildings, banks, railway stations, shopping malls, cinema hall, airport, different important locations of road, sacred places or different locations requiring a security presence. Once video footage is available then only task would be to monitor the movement of the suspect. The increase in processor speed, along with the decrease in price of high speed memory and data storage devices, there has been increased availability and applicability of computer vision and video processing techniques. Section II describes overview of the system, implementation of the present method has been described in section III, experiments conducted for this work along with results are described in section IV, and section V concludes this work.

II. OVERVIEW

Our investigation aims to establish an automatic gait recognition method based upon silhouette analysis measured during walking. Gait includes both the body appearance and the dynamics of human walking motion. Intuitively, recognizing people by gait depends greatly on how the silhouette shape of an individual changes over time in an image sequence. So, we may consider gait motion to be composed of a sequence of static body poses and expect that some distinguishable features with respect to those static body poses can be extracted and used for recognition by considering spatial variations of those observations.

For any recognition system, the feature extraction is the most important thing. Person's gait sequences need to be considered in such a way that the sequence can completely identify the person's walking style, which is discussed in subsection III *A*. As we are considering the silhouette images, the information relating to silhouettes are to be extracted. The edges of silhouette image have been extracted after applying edge detection technique and we are to find some points on the edge which would be used to represent a gait movement. After proper edge detection, corner detection technique will definitely work well because corner can be defined as a point for which there are two dominant and different edge directions in a local neighborhood of the point. The corner strength is defined as the smallest sum of squared differences between the patch and its neighbors i.e. horizontal, vertical and on the two diagonals, discussed in subsection III *B*. From these corner points we need to select some points in such a way that the gait signature of the person's silhouette is properly extracted and discussed in subsection III *C*. Distance between these points need to be calculated as these distance values are the features of the silhouettes. After extracting the features of silhouettes, they are stored in the database corresponding to their selected points in the form of matrices. After obtaining feature of the gait sequence of the testing person, it's being compared with the feature sequence available in the database, which is discussed in subsection III *D*. If the trained database contains the similar sequence then the video gets authenticated.

III. PRESENT METHOD

Like any trainable recognition system, this gait recognition system is also consisted of two phases namely training and testing. Taking a gait silhouette sequence of a person, edges of individual image in that sequence is detected after applying Sobel Edge detector [5][6][7]. From those edges, the closed contour of the individual is extracted. From the closed contour, the corner points are identified. There may be several corner points in an image, but we need to pick up a set of fixed points such that the set represents the uniqueness of an individual by which any individual can be discriminated from others. These points are called control points. A block diagram representing the training phase is shown in figure 1.

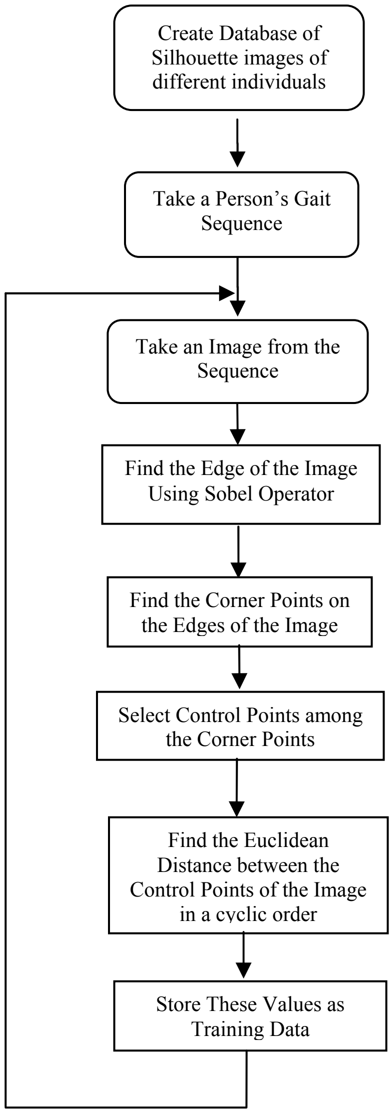

Figure 1. The block diagram for the training phase

Euclidean Distances between the Control Points in cyclic order are calculated and stored as features from that sequence. All these distance values from a sequence of images are kept in the database as training set for a person.

A. Gait Sequence

The database can be created by taking the video sequence of a person, then dividing this video sequence into different frames in such a way that the sequence can completely identify the persons gait style. Moreover, these images are the silhouette [8][9][10] images of persons to be included in the database. The silhouette of a person in the image can be obtained by background subtraction method [14]. Recognizing people by gait depends greatly on how the silhouette shape of an individual changes over time in an image sequence. To conduct experiments, we have used CASIA gait database, where the main assumption made is that the camera is static, and the only moving object in video sequences is the walker. The gait sequence can be obtained by taking the silhouettes in such a way that the object's posture in the first image will repeat in another image and the total number of images from the first to that repeated postured image make a sequence. Hence, to find a sequence, we accumulate all the images after recording the pose of the object in the initial image until the same pose is repeated in some image. For this database, the 26^{th} image's gait pose is same as first image and we have taken twenty six images of a person as a gait cycle. Such a sequence is shown in figure 2. It may be noted that, in the second sequence the images may not be in same pose as in the first sequence, i.e. first image's posture of the first sequence may not be same as that of first image of second sequence but it will be same with some another image later in that sequence. We have tested with the gait cycle of 50 persons.

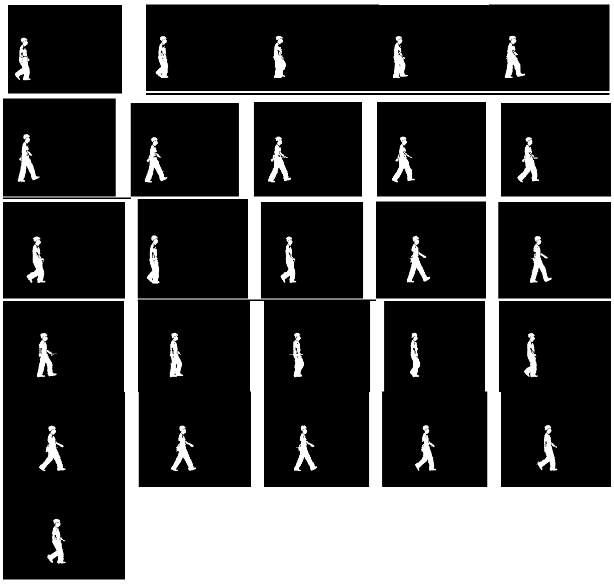

Figure 2. Complete gait cycle or sequence of a person

B. *Corner Detection*

Before we detect corner, we have detected edge of the image to find approximate contour of gait images. Edge detection [5][6][7][11][12][13] is a fundamental tool in image processing and computer vision, particularly in the areas of feature detection and feature extraction, which aims at identifying points in a digital image at which the image brightness changes sharply or, more formally, has discontinuities. Image Edge detection significantly reduces the amount of data and filters out useless information, while preserving the important structural properties in an image. Here, we have used Sobel operator [6] as a filter to detect edge of an image.

After detecting the edge of the silhouette, we find out the corner points on the edge. A corner can be defined as the intersection of two edges. A corner can also be defined as a point, for which there are two dominant and different edge directions in a local neighborhood of the point. In practice, most so-called corner detection methods detect intersecting points in general, rather than corners in particular. As a consequence, if only corners are to be detected it is necessary to do a local analysis of detected intersecting points to determine which of these real corners are. Examples of edge detection that can be used, with some post-processing, to detect corners are the Kirsch-Operator and the Frei-Chen masking set [14]. There are different types of method for corner detection e.g. Minimum Eigenvalue Method, Moravec corner detection algorithm [14], The Harris and Stephens corner detection method [14][16][17] etc. Minimum Eigenvalue Method is more computationally expensive than the Harris corner detection algorithm. Harris and Stephens improved upon Moravec's corner detector by considering the differential of the corner score with respect to direction directly, instead of using shifted patches. In order to exploit this improvised result, in this work, we have used the Harris and Stephens corner detection method to detect corner of the edge of the silhouette [15][16][17].

Let an image be given by I. Consider taking an image patch over the area (u, v) and shifting it by (x, y). The weighted sum of squared differences (SSD) between these two patches, denoted as S, is given by:

$$S(x,y) = \sum_u \sum_v w(u,v)\,(I(u+x,v+y) - I(u,v))^2 \quad \ldots\ldots.(1)$$

I (u+x,v+y) can be approximated by a Taylor expansion. Taking I_x and I_y be the partial derivative of I, such that

$$I(u+x, v+y) \approx I(u,v) + I_x(u,v)x + I_y(u,v)y \quad \ldots\ldots\ldots\ldots(2)$$

The approximation can be written as,

$$S(x,y) = \sum_{u} \sum_{v} w(u,v)(I_x(u,v)x + I_y(u,v)y)^2 \quad \ldots\ldots\ldots\ldots(3)$$

The equation (3) can be written in matrix form:

$$S(x,y) \approx (x\ y)\, A \begin{pmatrix} x \\ y \end{pmatrix} \quad \ldots\ldots\ldots\ldots\ldots(4)$$

where A is the structure tensor [17], given as

$$A = \sum_u \sum_v w(u,v) \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} = \begin{bmatrix} \langle I_x^2 \rangle & \langle I_x I_y \rangle \\ \langle I_x I_y \rangle & \langle I_y^2 \rangle \end{bmatrix} \ldots\ldots(5)$$

This matrix is a Harris matrix, and angle brackets denote averaging i.e. summation over (u, v).

C. *Selection of control points*

In this work, we have first extracted the contour of an image. We find the corners on this contour of each subject. Taking these corner points, we select a subset of those with a fixed number, called as set of control points. Then we find out the distances between them in a cyclic order and stored as a feature vector for that image. Similarly, for all the twenty six images of a gait sequence, feature vectors are extracted and stored in sequence to represent the feature vector set for the entire sequence.

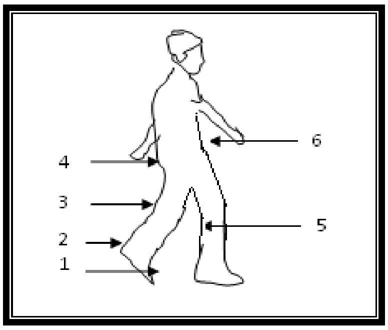

Figure 3. Control points 1, 2, 3, 4, 5 and 6.

Control point selection is very important and imperative in our paper of human identification by gait. From the corner points, we have chosen some points that will rightly characterize the person's gait characteristics.
In the figure 2, we can see the control points marked as 1, 2, 3, 4, 5, and 6 on toe, ankle, thigh, hip, knee, and waist respectively**.** Reason for selecting these points is that, respective positions of those points remain approximately constant for the same type of posture in different sequences but changes when the subject moves in a different posture and also, distinctly represents walking style of different individuals.

D. Testing

In case of testing, we follow the same technique for an unknown person's gait sequence and find out the distance values accordingly to compute the feature vector. Then this vector is compared with all such vectors stored in the database against a derived *threshold* value. If there is a match with any person's training sequence data then that person is identified, but if there is no match then we can infer that the data of that person is not available in our training set. The detail of the testing procedure is shown in figure 4.
The threshold value(T) is chosen in such a way that for the same person, after matching the training set with the testing set, it will rightly recognize the person, and for a different person, it will also recognize that both the person are not same. To declare a match between probe gait image and gallery gait images at least four control points, out of six, should match. This threshold value (T) has been identified experimentally.

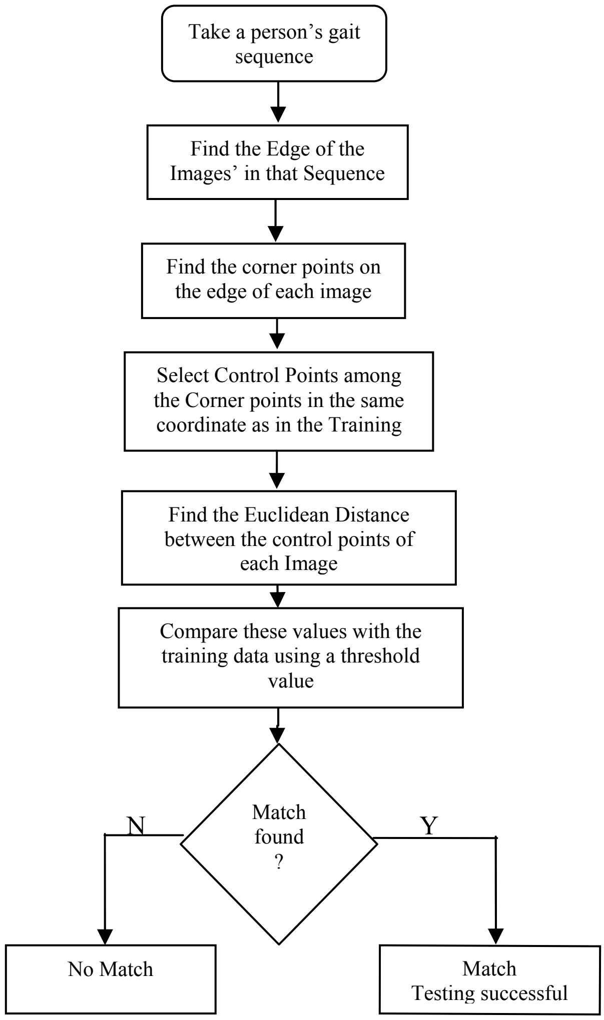

Figure 4. The Block Diagram describing testing

IV. EXPERIMENTAL RESULT

For experimentation, we have used CASIA gait database: dataset C. We conducted our experiment with gait sequence of 50 persons to examine the effectiveness of our technique. Here, we have given sample details of two individuals. Table I shows the data of 26 images of a person (say person-A). The first column denotes the image numbers and rest of columns are distances between the control points in cyclic order. For the same person, person-A, distances are also computed for another sequence and shown in Table II. After testing, we see the two different sequences of person-A matches. Since we have considered 26 images in a sequence, both in the training and testing database there should be a match with 26 images.
We computed the Euclidean distances between the coordinates of control points, as shown in figure 3, in a cyclic fashion i.e., calculated as between 1 & 2, 2 & 3, 3 & 4, 4& 5, 5 & 6, and 6 & 1. These distance values to be kept in the database as the training data for individual persons. There distances are used to compute the

threshold value, which would be used during testing. The ROC curve is drawn for this, which is shown in figure 5 and it has been found that the threshold value as 8.5 gives good result in terms of recognition. Table III shows the set of distances of another person (person-B) and that does not match with person-A.

Table I. Table contains the data of person-A of a sequence

Image No.	Distance between Control points					
	1-2	2-3	3-4	4-5	5-6	6-1
1	14.14214	10.04988	22.82542	56.04463	34.48188	44.01136
2	36.87818	7.28011	35.44009	23.85372	38.32754	61.35145
3	81.02469	7	38.32754	27.65863	87.28115	36.35932
4	28.44293	1.414214	68.18358	33.30165	78.31347	40.31129
5	35.0571	13	31.257	25.4951	60.82763	43.46263
6	10.19804	4	36.12478	58.18075	22.82542	40.31129
7	11.40175	1.414214	38.20995	23.85372	58.30952	19.31321
8	15.81139	1.414214	80.22468	50.77401	27.29469	23.85372
9	17.72005	1.414214	21.84033	88.29496	112.2854	18.68154
10	54.45181	1	27.51363	58.5235	11.31371	91.78235
11	10.44031	7.28011	46.32494	54.78138	84.48077	25.05993
12	21.9545	6.082763	34.9285	73.08215	17	91.09336
13	16.12452	8	86.49277	71.30919	58.13777	79.84986
14	82.9759	6.324555	36.71512	23.76973	55.9017	98.03061
15	76.29548	6.708204	16.27882	75.18643	83.29466	23.02173
16	101.7104	6.708204	32.89377	54.40588	26.24881	61.03278
17	78.31347	5	37.36308	49.0408	113.1106	105.3233
18	26.07681	12	45.27693	98.65597	38.47077	22.02272
19	31.257	10.04988	48.25971	21.09502	60.29925	24.41311
20	21.37756	1.414214	94.19129	86.68333	11.31371	15.0333
21	72.1734	16.03122	80.30567	18.24829	101.4938	28.30194
22	79.40403	8	43.17407	25.45584	65.37584	91.44397
23	14.31782	7	87.69265	25.23886	14.86607	85.61542
24	11.18034	2.236068	13.45362	98.48858	10.19804	86.58522
25	54.57105	8.062258	14.31782	99.24717	84.85281	23.08679
26	16.87818	7.28011	35.44009	23.85372	38.32754	51.35145

Table II. Table contains the data of person A of another sequence

Image No.	Control Points					
	1-2	2-3	3-4	4-5	5-6	6-1
27	71.19691	6.082763	91.24144	21.09502	10.63015	76.2168
28	62.39391	6.082763	74.43118	56.85948	29.54657	52.55473
29	64.03124	13	26.68333	42.48529	104.1201	44.72136
30	54.07176	19.06524	15.41639	23.12714	52.80127	15.5125
31	11.31371	50.24938	106.3015	115.2085	19.10497	23.4094
32	14.56022	5.09902	52.23983	37.57659	21.84033	15.29706
33	52.46904	5.09902	73.68175	31.241	32.98485	83.9345
34	8.485281	1.414214	24.69818	69.57011	21.09502	108.8531
35	17.49286	2.236068	45.22168	49.64877	15.81139	94.59387
36	16.15549	7.211103	36.67424	30.52868	13.45362	66.24198
37	53.45091	6.324555	57.24509	25.96151	8	59.20304
38	16.27882	8.544004	13.0384	101	7.615773	100.4241
39	64.13267	11.40175	106.7942	64.62198	54.12947	102.3572
40	49.64877	4	103.9471	82.46211	29.83287	58.59181
41	80.025	17	30.41381	23.02173	37.10795	20.24846
42	55.08176	29.01724	19.41649	70.00714	62.80127	25.6125
43	73.06162	8.062258	50.08992	65.80274	25.70992	20
44	17.46425	4.123106	27.65863	38.27532	46.87217	22.2036
45	51.97115	1.414214	36.68787	65.14599	11	99.0404
46	8.062258	8	32.57299	52.80152	63.15061	26.24881
47	13.89244	5.09902	34.9285	39.05125	39.84972	36.12478
48	17.08801	5	76.92204	30.88689	49.47727	112.8938
49	54.23099	6.082763	23	59.09315	8.485281	72.67049
50	41.14608	8.062258	74.72617	39.44617	47.67599	90.82401
51	63.06346	2	38.07887	52.92447	21.54066	31.257
52	66.27882	6.082763	80.51828	24.29447	12.95281	80.00625

Table III. Table contains the data of person-B of a sequence

Image No.	Distance between Control Points					
	1-2	2-3	3-4	4-5	5-6	6-1
1	38.60052	10.04988	41.4367	24.20744	38.8973	24.69818
2	36.13862	5.09902	15.55635	25.23886	73.68175	73.37575
3	16.27882	16.03122	44.28318	34.1321	71.06335	20.09975
4	59.07622	11.04536	44.72136	69.64194	28.86174	20.61553
5	42.04759	49	25.31798	35	54.12947	101.2028
6	17.46425	4.123106	52.23983	51.07837	8.544004	97.49359
7	27.89265	4.123106	29.12044	35.80503	40.60788	27.80288
8	27.20294	10.04988	15.6205	110.0227	13.45362	88.76936
9	55.7853	11.04536	51.24451	40.81666	10.19804	30.52868
10	25	6.082763	36.23534	33.94113	14.76482	76.92204
11	26.1725	6.324555	56.64804	28.79236	59.5399	109.2016
12	18.02776	8.944272	29.20616	28.4605	21.40093	32.14032
13	68.65858	4	38.01316	38.91015	67.74216	24.08319
14	35.13662	5.09712	15.54635	25.23226	73.18175	73.33475
15	96.13012	6.082763	20.24846	27.20294	76.10519	75.43209
16	16.12452	30.08322	46.27094	29.83287	78.31347	19.23538
17	59.03389	68.00735	8.246211	22.82542	67.18631	50.92151
18	48.16638	12	37.48333	38.07887	51.62364	25.4951
19	34.71311	13.0384	76.53104	21.0238	10.63015	94.14882
20	31.01612	8	62.8172	42.94182	89.27486	115.447
21	19.23538	6	56.29387	40.31129	74.67262	27.20294
22	31.38471	6.082763	61.03278	27.313	32.75668	87.23531
23	52.20153	6.082763	76.24303	33.42155	18.78829	79.75588
24	17.72005	9.055385	102.9612	60.16644	41.59327	92.84934
25	21.63331	7.615773	70.34202	39.96248	50.35871	90.24965
26	31.19691	6.082763	45.24144	21.09502	10.63015	26.2168

Table IV. Different recognition parameters (for threshold, T= 8.5)

Person	Correct Recognition rate	Correct Rejection	False Acceptance Rate (FAR)	False rejection Rate (FRR)	Equal Error Rate (EER)
50	84%	83%	16%	16%	0.16

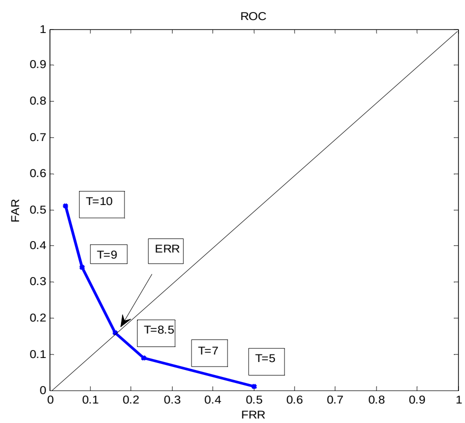

Figure 5. ROC Curve

V. CONCLUSION

With strong experiential evaluation, this paper focuses on the idea of using silhouette-based gait analysis. With the increasing demands of visual surveillance systems, human identification at a distance has recently gained more interest in the field of image processing and pattern recognition. Gait is a potential behavioral feature and many allied studies have demonstrated that it has a rich potential as a biometric for recognition. Gait is sensitive to various covariate conditions, which are circumstantial and physical conditions that can affect either gait itself or the extracted gait features. Example of these conditions includes carrying condition (backpack, briefcase, handbag, etc.), view angle, speed and shoe-wear type and etc. In this work, we have used only six control points. There is a scope of extension in number of control points. Also, for classification for feature vectors support vector machine (SVM) can be employed in future.

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