A Preliminary Study of Gait-based Age Estimation Techniques

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***Abstract*— Gait recognition is an emerging biometric technology due to the widespread use of closed-circuit television (CCTV) camera. Owing to the non-cooperative nature of CCTV setting, gait appears to be a valuable cue that can be extracted from the video footage. The gait feature extracted from the video can be used for several applications such as person authentication for security access control and walking pattern examination for medical analysis. In this paper, we explore the use of gait signature for age estimation. As this is a very new research area, there are not much gait-based age estimation techniques in the literature. Hence, this paper provides a study of the allied of works related to gait-based age estimation, ranging from medical to computer vision domains. Based on our study, several distinctive gait features that can be used for age estimation are identified. These features include stride length, stride frequency, head length, body length, head-to-body ratio, leg length and stature. Preliminary experiments conducted using the OU-ISIR Large Population gait database show that the proposed features could distinguish two age groups, namely adult and child, effectively.**

I. INTRODUCTION

Human gait recognition, often described as the manner of walking, has attracted increased attention, especially from the computer vision community recently. Human gait recognition enables intelligent surveillance security system to take place at a distance, without interaction of the subjects with the system at all. Gait can be used in most circumstances as gait is hard to conceal and it can be performed under low resolution video. These are the reasons why this technology has become popular and more new techniques have been developed to flourish the related studies.

A number of gait-based techniques have existed for quite some times ([1], [2], [3] and [4]), but most of them are used for human identification and recognition. Nevertheless, medical and psychological studies have shown that gait feature also contains age discriminative information. For example, Davis [5] and Maliszewski et al. [6] show that there are differences between adult and child in terms of speed where it involves leg length, stride width and stride frequencies. Besides, Ince et al. [7] demonstrated that a child can be differentiated from an adult based on the head-to-body ratio. These studies suggest that it is possible to employ the gait and biological features of the human body to estimate the age of a person.

Gait-based age estimation is a very new research area. In the field trials to date, there is only one study by Lu and Tan [8] that exclusively studies the application of gait features for age estimation. Two types of Gait Energy Images (GEIs) were fused to obtain the age of the subject. This study suggests that it is possible to apply the existing gait-based techniques like [1], [2], [3] and [4] to extract appropriate features from the gait sequence, and use these features to estimate age.

In this paper, we have identified several gait signatures such as head length, body length, leg length and stride width that can be used for age estimation. We have also employed other biological features of the human body such as head-to-body ratio as a complimentary age discriminative feature. We focus on two age groups namely adult and child. Experiments using the OU-ISIR Large Population Database shows that the proposed gait features are effective against discriminating the two age groups.

II. RELATED WORK

Evidences have shown that gait features can be used for age estimation. However, there are limited number of studies that explore the use of gait for age estimation. We provide a comprehensive review of the allied of studies related to this area. In particular, we first study the existing gait-based techniques which mainly extract gait features for person recognition. After that, we review the state-of-the-art age estimation techniques. These techniques are primarily based on the analysis of the face features to perform age estimation. We have also provided a study about human biological and kinematic features that can potentially be used for age estimation from the medical perspective. By generalizing these diverse areas of studies, we hope to provide a unified direction to engage different realms to solve the age estimation problem using gait feature.

A. Gait Signature Extraction And Recognition

There are several existing gait extraction techniques that are suitable for age estimation. Overall, these techniques can be categorized into two types: motion-free [9] and model-based [2]. There are also hybrid techniques that use both of the methods [1].

Han and Bhanu first proposed the idea of GEI, a compact spatio-temporal for gait representation [10]. GEI is known for its high robustness and excellent performance. It not only saves memory and computing time, but is also insensitive to noise. The initial result reported on a gait database consisting of 122 subjects yield a promising accuracy rate of more than 90%. Dupuis et al. [11] further extended the work of Han and

Bhanu. They performed feature selection on the GEI using Random Forest (RF) to save computational resources while retaining or improving the classification algorithm. Canonical Discriminant Analysis (CDA) and Multiple Discriminant Analysis (MDA) were used to classify the processed GEI. There are other enhancements over the basic GEI like Enhanced GEI [12], Frame Difference Energy Image [13], Active Energy Image [14], and Pose Energy Image [15].

The model-based approaches deploy some structural or motion models to characterize human gait. Tafazzoli and Safabakhsh [4] deployed a different approach to model walking pattern using the leg and arm movements. They used a shape model estimation based on anatomical proportions to construct a posterior model for the movement of body parts. A motion model estimation method was developed to extract the leg and arm angles. Jean et al. [2] proposed a five-point human model to automatically locate the positions of the human body. They used a motion correspondence algorithm and legs separating algorithm that scanned for the legs position. A foreground-background-foreground (FBF) pattern was used to track the feet because the corresponding room between two feet could represent the space between the legs. As for hand tracking, an overlapping bounding box algorithm based on skin color was applied. For head tracking, the pixel at top position of the silhouette or the mass center of a region was deployed. The proposed method seems to be promising to be implemented in an uncontrolled real-time environment.

There are also studies that combine the model-free and model-based approaches. Zhang et al. [1] introduced a hybrid techniques that used the Metropolis-Hasting method to extract gait features from the image sequences. A five-link biped locomotion human model was also deployed to describe the motion pattern. According to them, frequency domain-based representation is suitable due to the cyclic nature of gait. Four space domain features namely ankle elevation, knee elevation, ankle stride width, and knee stride width were employed. Discrete Fourier Transform was applied on these four features to reveal the periodic components in the gait sequence. Another work presented by Wang et al. [3] also belongs to the hybrid approach. The static and dynamic body parts were fused to achieve higher accuracy. They represented silhouette information using Procrustes shape and obtained eigenshape of the body appearance. This was considered as the static information for gait. They also used a human body motion model to track the subject. The joint-angle trajectories of lower limbs were recovered which was then used as dynamic information for gait. Both of the static and dynamic features were fused at decision level to achieve the final score. A comparison of the gait signature extraction techniques is shown in Table I.

TABLE I
COMPARISON OF GAIT SIGNATURE EXTRACTION TECHNIQUES

Methods	Gait Feature Representation	Feature Extraction and Classification	Dataset	Based Type
Han & Bhanu [10]	Spatio-temporal: GEI	Silhouette distortion analysis, Fusion of real and synthetic templates	USF	Model-free
Dupuis et al. [11]	GEI	RF, CDA, MDA	CASIA GEI	Model-free
Tafazzoli & Safabakhsh [4]	Leg and arm movements, anatomical proportions	Shape model estimation, Motion model estimation, KNN	Georgia Tech	Model-based
Jean et al. [2]	Head, hand and feet	Five points human model, FBF, Motion correspondence algorithms, Bounding box overlap algorithm (skin color), Mass center of a region of the upper silhouette	Real-time	Model-based
Wang et al. [3]	Body shape, Limbs and joints	Fusion of static and dynamic information, Procrustes shape analysis (static), human body motion model (dynamic), NEP classifier	Own Dataset (20 subjects)	Silhouette + Model-based
Zhang et al. [1]	Space-domain feature: ankle and knee (elevation, stride width)	Five-link biped locomotion human model, Metropolis-Hasting method, DFT, HMM	USF, CMU	Silhouette + Model-based

B. *Age Estimation*

Techniques for age estimation have been around for some time, most of which are face-based. Age estimation using the face can be performed under two conditions: static and unconstraint. Static means that the system either requires a controlled environment or the subject's interaction; while unconstraint means the opposite.

Han et al. [16] performed age estimation from the perspective of face aging. They extracted some Biological Inspired Features (BIF) from the face. The BIF were classified into four disjoint age groups using a binary decision tree based on SVM (SVM-BDT). A separate SVM age regressor was trained in each groups to predict the final age. By combining the results from the different stages, an overall accuracy of 74.8% could be achieved.

Zhang et al. [17] proposed a patch-based Hidden Markov Model (HMM) supervector to represent age patches of the face images. Each image patch was calculated using a patch-based HMM supervector. By using nearest centroid classifier, the difference between the images was characterized by pairwise Euclidean distances between the supervectors and each image was then classified into its respective age class.

Han and Jain [18] presented an age estimation method that works under unconstrained conditions. The input images were real-life face images in the wild. They started with face normalization by performing pose and photometric corrections on the input image. Then, they extracted BIF from the normalized input image which included the central face region and the surrounding context region. Lastly, the extracted feature was input to three SVMs which were used to separately predict the age group of the subject.

Khryashchev et al. [19] proposed a multiclass classification approach for age estimation. They preprocessed the face images using color space transformation. The face images were then transformed to the local binary patterns (LBP) feature space. They used SVM training procedure to construct a binary classifier for age estimation.

The methods discussed thus far were based on human face. Currently, there are not much existence of age estimation technique using gait, except for [8]. Lu and Tan extracted the GEI from each gait sequence [8]. Then, they extracted the Gabor Magnitude (GM) and Gabor Phase (GP) from the GEI. A label encoding scheme was devised to convert each age value into a binary label sequence. The binary label sequence was then input into a multilabel-guided (MLG) subspace to reduce the dimension of the features. Lastly, multilabel k-nearest neighbors (ML-KNN) was adopted to classify and decode the label vector information for its final result. The proposed approach reported an average mean square error of 6. Table II presents a comparison of the different methods working towards age estimation.

TABLE II
COMPARISON OF AGE ESTIMATION TECHNIQUE

Methods	Feature Extraction and Classification	Dataset	Type	Modality
Zhuang et al. [17]	Patch-based HMM supervector, nearest centroid classifier	4000 images (800 males), 4000 images (800 females)	Static	Face
Han et al. [16]	Component BIF, SVM-BDT, Hierarchical age estimation, Age estimation fusion	FGNET, MORPH II, PCOS	Static	Face
Khryashchev et al. [19]	LBP	Private RUS-FD, MORTH, FG-NET	Un-constraint	Face
Han & Jain [18]	Pose and photometric corrections, BIF, SVM	IOG, LFW+	Un-constraint	Face
Lu & Tan [8]	GEI , GM, GP, Label encoding algorithm, MLG subspace, ML-KNN classifier,	USF	Un-constraint	Gait

C. *Biological and Kinematic Features*

Studies have shown that several biological and kinematic features from the human body can be used clues to predict the age of a person. Ince et al. [7] demonstrated that it is possible to classify a child and an adult using ratio of the head and body height. The subject was detected using Haar-like feature trained with Adaboost algorithm. Haar Cascade Detector was applied to detect the subject's head and body. After that, the head and body ratio was calculated and this ratio was used to determine whether the subject was as an adult or child based on a threshold value.

Maliszewski and Freedson [6] studied the differences between adults and children while running. They suggested that boys have higher stride frequencies than men using absolute speed (ABS) and relative speed (REL). Not only that, boys have higher stride or leg length during absolute speed while men have higher stride during relative speed. A one-way analysis of variance (ANOVA) was used to determine the value differences between adults and children. Hence, the relations in the adult and child stride length were determined statistically.

A work by Davis [5] demonstrates that children's stride frequencies usually fall in the range of 55.3 to 89.8 strides per minute; while the adults' are in the range of 36.7 to 73.3 strides per minute. As for their relative strides, both children and adults have almost the same range of 0.27 to 0.55. This data suggests that it is possible to distinguish a child from an adult based on their stride information. Table III shows a summary of works that suggest different biological or kinematic features from the human body that can be used for age estimation.

TABLE III
COMPARISON OF BIOLOGICAL AND KINEMATIC FEATURES

Methods	Biological/ Kinematic Feature Representation	Dataset	Type
Ince et al. [7]	Head, Body, Head-over-body ratio	INRIA, CVC-CER-01	Biological
Maliszewski & Freedson [6]	Leg length, Stride length, Stride frequencies, Relation in stride length	-	Kinematic
Davis [5]	Stride Frequency, Relative Stride, Trajectories of Marked Head and Ankle positions	Own Dataset (6 children, 9 adults)	Kinematic

III. PROPOSED METHOD

In this paper, the silhouette images are used to represent a gait sequence due to their robustness against low resolution images. The use of this representation is appropriate as CCTV footage is often of low quality. Several biological and kinematic features are chosen from the silhouette image to represent age-discriminative features. The biological features identified include head length, body length and leg length, as suggested by [6] and [7]. As for kinematic feature, stride frequency and length are chosen [5] and [6]. We manually identify and label the body parts and joint positions from the silhouette images.

Fig. 1 shows an example of the marked landmark points on the human body. The head length l_h is measured from the top pixel of the silhouette image (x_T, y_T) to the pixel near the subject's chin (x_C, y_C) by using,

$$l_h = \sqrt{(x_T - x_C)^2 + (y_T - y_C)^2} \quad (1)$$

Similarly, the body height, l_b, is measured from the chin to the ground position, and the stride length, s_L is measured from the back of the subject's feet to the other back of the feet. On the other hand, measurement of the leg length is more complicated as it involves the calculation of joint positions. We use two line representations to measure the feet. The first line is measured from the thigh to knee level; while the second line is measured from the knee to the lowest part of the foot. The same measurement is applied on the other leg. Let a_1 and a_2 be the first and second half of the first leg; while b_1 and b_2 represent the first and second half of the second leg. The length of the leg, l_g is calculated as

$$l_g = \frac{(a_1 + a_2) + (b_1 + b_2)}{2} \quad (2)$$

The other measurements of the gait features can be derived from these basic features. Let t, sf, and r denote the stature, stride frequency and head-to-body ratio of the subject. These features can be computed as

$$t = l_h + l_b \quad (3)$$

$$sf = \frac{s_L}{N}, N \text{ is the number of frames per cycle} \quad (4)$$

$$r = \frac{l_h}{l_b}, \text{ where } 0 < r < 1 \quad (5)$$

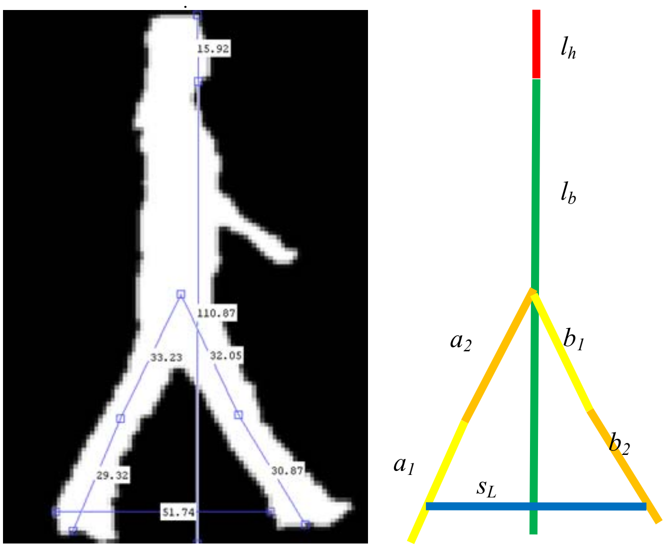

Fig. 1 Measurement on one of the subject's silhouette images.

IV. Experiments and Discussions

A. Experiment Setup

We subsampled a dataset from the Large Population OU-ISIR gait database [20] collected by the Institute of Scientific and Industrial Research (ISIR) of Osaka University. It is the current world's largest gait database which includes 4007 subjects, consisting of 2135 males and 1872 females. As we are concern about the age factor, this database have ages ranging from 1 to 94 years old. Fig. 2 shows the distributions of the subjects' gender and age information, which are the only information we have about the database content.

There are several advantages for using this dataset. First, it is almost twenty times the size of the largest publicly available gait database, providing enough subjects for almost any tests or experiments. Besides, it has a good gender balance with the ratio of males to females close to one. In addition, the wide range of ages from 1 to 94 years old provides an almost ideal dataset for testing. With these characteristics, the dataset servers as an ideal performance evaluation in our case to verify the reliability of the proposed gait-based age estimation method.

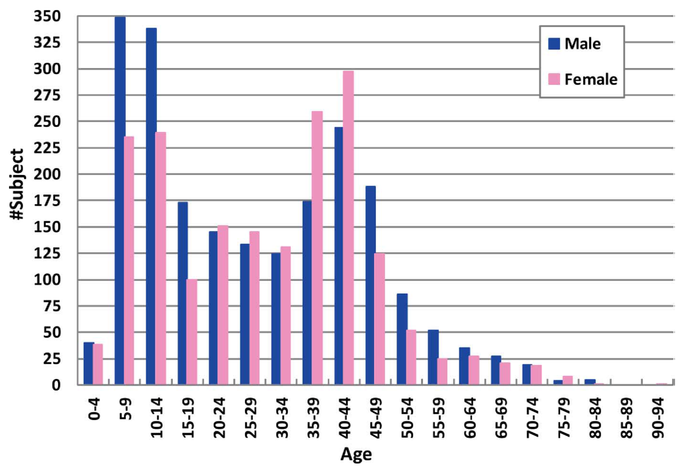

Fig. 2 Distributions of the subjects' gender and age in OU-ISIR Database [15].

Twenty sequences from twenty different subjects are chosen manually by human eye from the database. The selection has to be done manually because the age information for each individual subjects in the dataset have not been released yet. The selected subjects consist of ten adults and ten children with one sequence per subject. The chosen camera angle is 85 degree which provides a clear view on each of the body configurations. The silhouette images are normalized to a resolution size of 88x128 pixels (width to height). Since the silhouette images provided in the database are quite high in quality, they are directly used in our experiments.

B. Investigating the Usefulness of Biological and Kinematic Gait Features

In the first experiment, we investigate the feasibility of deploying the head-to-body ratio to distinguish a child from an adult. Fig. 3 shows the head-to-body ratio for children and adults. We observe that adults have a ratio range of 0.15 to 0.16 while children have a ratio range of 0.19 to 0.26. In general, most adults have the ratio peaks around 0.16 and those for children is mostly over 0.20. The result shows that head-to-body ratio is a distinguishable feature to differentiate the adult and children subjects.

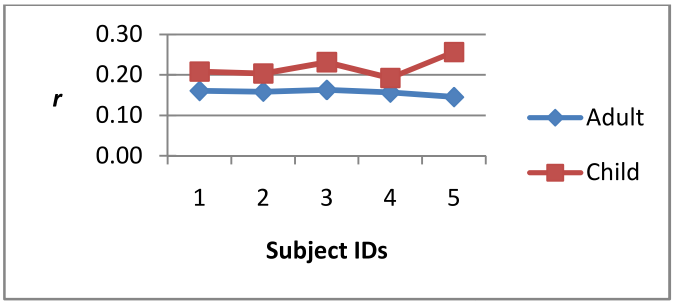

Fig. 3 Relation of head-to-body ratio between adult and child

In the next experiment, we analyze the usefulness of stride frequencies, *sf*, for our study. Table IV depicts the measurement statistics for the different gait features of ten randomly selected subjects. We observe that *sf* stays consistent for all the subjects. This is most probably due to the short walking distance of the collected videos or the small difference in walking speed. However, we can clearly observe the point when the subject is opening or closing the stride due to the change of stride length, s_L. We can determine *sf* by detecting the turning point of s_L. A turning point is identified when s_L reaches the peak or bottom values.

Stature, *t*, is observed to be almost around 127 pixels in height and it would not go higher as the maximum size of the silhouette image resolution is 88x128 pixels. It is predicted to be the same for adult and child as the images have been normalized. Leg length, l_g, of the subjects do not deviate much, but we can still observe that children have shorter leg proportion as compared to adults. Besides, the body length, l_b, of the two age groups also portray distinguishable patterns. In summary, we observe that s_L, l_g, l_b, and *r* play crucial roles in differentiating the two age groups. Other feature like l_h can be used as complementary feature for age estimation.

TABLE IV
SUMMARY OF THE SUBJECTS MEASUREMENT

#	*Age group*	l_h	l_b	l_g	t	sf	s_L	r
1	Adult	17.63	109.89	64.56	127.53	2.00	55.18	0.16
2	Adult	17.42	109.96	62.69	127.38	2.00	47.10	0.16
3	Adult	17.83	109.45	62.82	127.28	2.00	54.49	0.16
4	Adult	17.13	109.64	66.65	126.77	2.00	59.21	0.16
5	Adult	16.05	110.55	61.30	126.59	2.00	56.60	0.15
6	Child	21.97	105.64	60.90	127.61	2.00	47.93	0.21
7	Child	21.36	105.21	60.99	126.56	2.00	56.58	0.20
8	Child	23.87	103.23	57.39	127.10	2.00	58.00	0.23
9	Child	20.43	106.15	59.64	126.58	2.00	56.86	0.19
10	Child	25.88	101.07	57.46	126.95	2.00	46.17	0.26

C. Correlation Matrix for Adult and Child

Next, we study the correlation among the features. The threshold is set to 0.50 which means we are only interested in notable relation that can convey meaningful information (with any correlation greater than 0.50 or smaller than -0.50). The threshold is set to be balanced across the range from -1 to 1. Fig. 4 and Fig. 5 show the correlation matrices of the adult and child, respectively. The correlation matrices for both classes show that the head, stature and head-to-body ratio are positively correlated. This is expected as stature is the sum of head and body. On the other hand, the body height is negatively correlated to head, stature and head-to-body ratio. This result shows that the body height is distinguishable from the other features. We also observe that head-to-body ratio is the best feature to be used for classification of adult and child. Other than that, there is no obvious relation among the other features, except for stride length and stature. The stride length and the stature are negatively correlated which means the higher the stature, the lower the stride length. In our case, however, this cannot been applied as our silhouette images are normalized. In general, the observations we found in this experiment agree with the previous analysis.

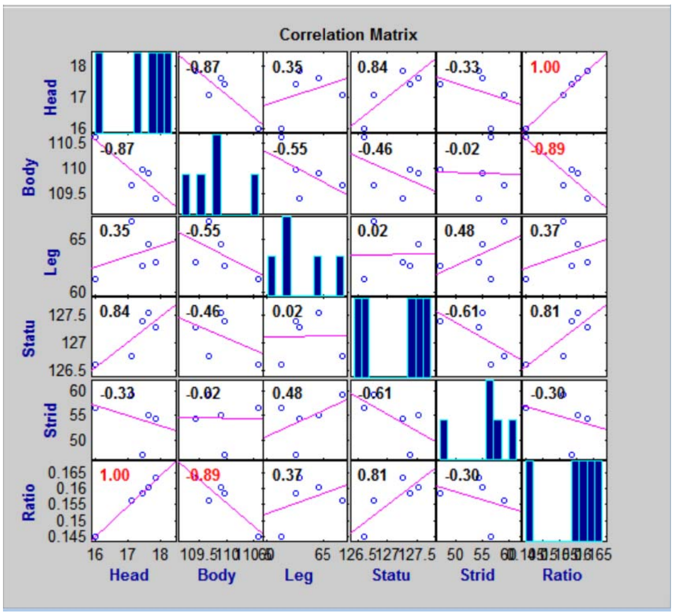

Fig. 4 Correlation Matrix of Adults.

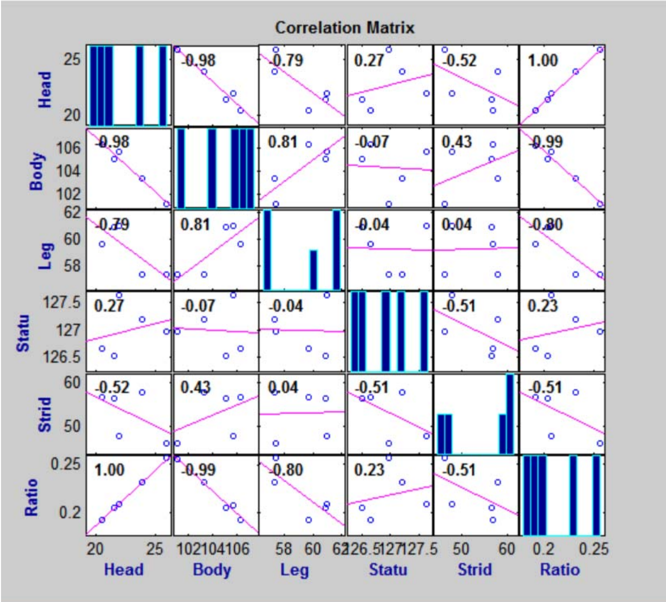

Fig. 5 Correlation Matrix of Children.

D. SVM Classification

We have also conducted a test to classify the age group of a subject using SVM. A simple linear kernel is adopted. The measurements of each subject like l_h , l_b , and r are concatenated to form a feature vector. Two samples for each group are randomly selected for training, while the remaining for testing. The random division between the training and testing samples are repeated for ten times and the average results are recorded.

Experiment result shows 100% accuracy in the preliminary test. Fig. 6 illustrates the classification results of the two age groups (randomly selecting the r and s_L features for a 2D illustration). The two age groups can be separated clearly using a linear separator. The good result may due to the small number of subjects in the experiment. Nevertheless, we conjecture the performance might drop when we conduct a thorough test using the complete OU-ISIR gait database with the same approach but much larger number of subjects (more than 1000 subjects).

V. Conclusion and Future Work

In this paper, we demonstrate that human biological and kinematic features such as stride length and head-to-body ratio are able to distinguish a child from an adult effectively. We show that it is possible to merge diverse studies related to human gait for age estimation. However, it is challenging to develop a fully automated system for this purpose. Issues such as self-occlusion poses a great challenge. In future, we will run a thorough experiment on the entire OU-ISIR Large Population dataset once the age and gender information are released by ISIR of Osaka University. We also hope to develop automated processes to extract and measure the body features for age estimation and classification.

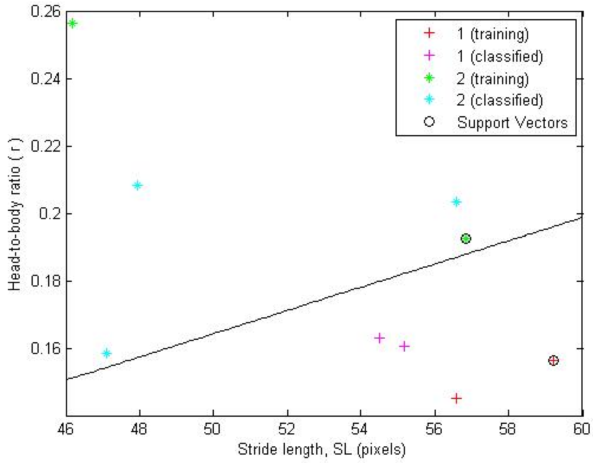

Fig. 6 Sample classification result using SVM with linear kernel.

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