PEOPLE IDENTIFICATION USING SHADOW DYNAMICS

Yumi Iwashita†, Adrian Stoica‡, Ryo Kurazume†

† Information Science and Electrical Engineering, Kyushu University, Japan
‡Jet Propulsion Laboratory, California Institute of Technology, USA

ABSTRACT

People identification has numerous applications, ranging from surveillance/security to robotics. Face and body movement/gait biometrics are the most important tools for this task. Traditional biometrics use direct observation of the body, yet in some situations a projection may offer more information than the direct signal, for example the shadow of a person observed from overhead, e.g. from an unmanned aerial vehicle, may contain more detail than the top view of the head/body. We introduced the idea of $shadow\ biometrics$, exploiting biometrics information in human shadow silhouettes as derived from video imagery; this enables ”overhead biometrics”, for recognition of human identity and behavior from high altitude airborne platforms using overhead video sequences. In this paper, we provide a demonstration of person identification based on gait recognition from shadow analysis. We describe compensation steps to address shadow variation with conditions of observation (sun position, etc). We define measures of shape variation, such as horizontal stripes on the silhouette, their length change in time determines frequency components (here spherical harmonics) for each gait cycle, which are used for classification by a k-nearest neighbor classifier. A correct classification rate (CCR) of 95 % was obtained. A degradation of CCR from 95 % to 75 % was observed when reduced spatial and temporal resolution from 1cm to 2cm, and from 30fps to 15fps.

***Index Terms*—** Shadow biometrics, gait, people identification, spherical harmonics

1. INTRODUCTION

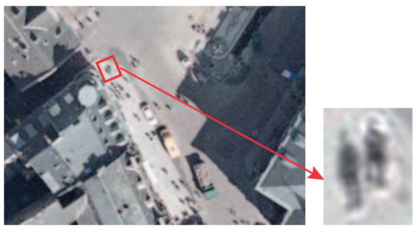
People identification has numerous applications. At one end of the spectrum are surveillance applications for intelligence and security operations, while at the other end are personal robots that need to recognize their owners and users. Recognition is based on classification using human biometrics features, such as face or gait. While traditional biometrics rely on direct observation (e.g. image of the face/body), it may be the case that a projection may have more information than the direct signal. For example, the shadow of a person observed from a higher point, or from overhead, as from the unmanned aerial vehicle. We proposed the exploitation of biometrics information in human shadow silhouettes (shadow biometrics). Centimeter-level resolution of airborne sensing systems enables people identification from high altitudes. Although two individuals seen from above may appear indistinguishable, in particular if wearing similar head covers and robes, their shadow silhouette often offers a larger area and almost certainly more accurate body movement details head and shoulder top view. Fig. 1 shows an image above a city; what appears to be the shape of a human body is in fact the shape of its shadow, a body projection. Shadows offer the connecting link between aerial observation and gait/biometrics/gesture and behavior classification. Shadow biometrics technology [1] (simply defined as biometrics using information from shadows) opens a new research area of applications in ”overhead biometrics”, which includes the remote observations from airborne/space platforms of biometric characteristics.

Shadow biometrics was proposed in [1]. Here we present further details, including how to compensate for variations in observation conditions. The video/image processing greatly benefits from advances in two main areas: shadow detection/segmentation techniques, that allow extraction of the shadow silhouette, and gait analysis techniques, which extract the information from silhouette movements.

Significant progress has been achieved recently for human detection and identification. Although there is a large diversity of gait recognition algorithms, a majority have focused on canonical (side) viewing point using silhouettes for human detection or identification, with several public databases available. Silhouette gait recognition approaches generally fall into two main categories [2]: (1) model-free shape-based analysis, and (2) model-based structural analysis. Shape-based analysis uses measurements of spatio-temporal features of the silhouette. To characterize shape and its variations different measures may including size (width, height, area), angles between lines (e.g. foot/ankle, upper arm-lower arm), higher order moments around the centroid, measures of symmetry, or other shape representations, and temporal variations such as cyclic oscillations at the stride frequency. Shape-based approaches have been shown very effective for human silhouette detection and have been used with good results on human identification.

Structural model-based approaches include parameterization of gait dynamics, such as stride length, cadence, and stride speed. Static body parameters, such as the ratio of sizes of various body parts, can be considered in conjunction with these parameters. Traditionally, these approaches have not reported high performances on common databases, partly due to their need for 3D calibration information.

In this paper we outline the main aspects of shadow biometrics and illustrate with method with results. Section 2 offers details about the database to provide a demonstration of the human gait recognition from shadow analysis. Section 3 describes the methodology with particular detail on compensation needed. We introduce here the compensation with the position of the sun, geographic location, etc. Section 4 presents the results. The demonstration of person identification is for subject walking only in one direction, the extension for other directions being work in progress. Section 5 offers concluding remarks.



(a) (b)

Fig. 1. (a) Remote sensing imagery (Google), (b) magnification of smaller window. What looks like humans are shadows.

2. SHADOW GAIT DATABASE

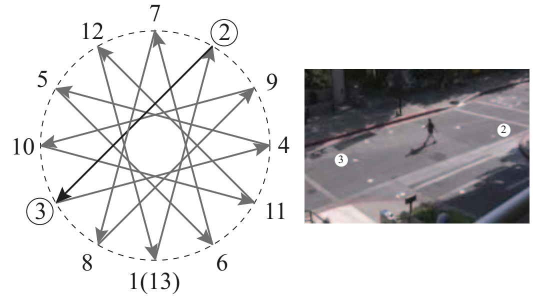
An operational system would rely on recording imagery from a sensor, which could be located on a robot or unmanned aerial platform at altitudes as high as 10,000 m, processing to extract features and using these data compared with a database for the purpose of classification. In our experimental database we recorded from an angle, but various means - including recording from directly overhead, which could be closer to some real-world application, or even using conventional video from lateral and then transforming this silhouette for the database.

A shadow database was created based on imagery recorded with a video camera positioned on an upper floor of a building. Five subjects were recorded at approximately the same time of the day (a few minutes difference) while walking in different directions, in a sequence of walks that changed by 150 degrees when turning (in trigonometric sense, left u-turn), in a specific sequence that maximizes collecting data in various directions for a limited area (see Fig. 2). About 8 to 10 steps were walked in each direction. The ground resolution is approximately 1cm per pixel. There are 30 frames per second.

Fig. 2 (a) illustrates the set-up diagram and shows a photo of the real-world set-up, with white markers placed on the ground to indicate the star points (directions of walk and turning points). Fig. 2 (b) illustrates an example image of walking. The current implementation uses a single (arbitrary) direction of walk for each individual; this will be expanded for use of all directions.

3. METHODOLOGY

This section describes the methodology used in our work. To summarize, the main steps of processing are: (1) background



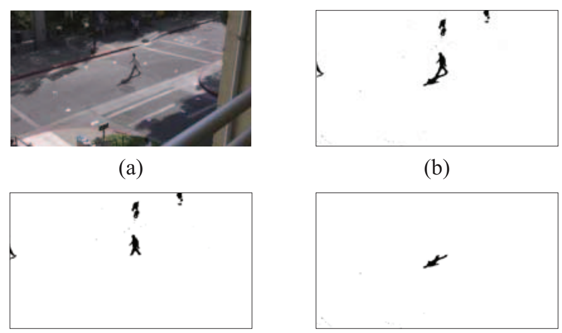
(a) (b)

Fig. 2. (a) A 12 point star marking on the ground. (b) Image illustrating the real world set-up, and person walking, with shadow visible.

subtraction and segmentation of people and shadows, (2) standard silhouette reconstruction (to compensate for variations in position of sun/light source), (3) determine shadow-metrics (features), (4) analyze dynamics of features and classification. The following offers more details on the methods used.

3.1. Segmentation

To extract shadow silhouettes from images in the database, firstly a background subtraction [3] is used. Fig. 3 (b) shows an example of extracted silhouettes, from the original image shown in Fig. 3 (a). In this work we separated the body and shadow regions manually (Fig. 3 (c)); this should be performed automatically in future work.



(a) (b) (c1) (c2)

Fig. 3. (a) A sample from the database, (b) its extracted target region, (c) body and shadow regions.

3.2. Compensations/scaling to a ”standard” silhouette

One needs to compensate for different shadow angles/sizes based on the position of the sun (or more generic, the light source), position of person and observation camera, from known time of the day, inclination of the sun rays from time/position of the sun for given longitude/latitude, position of the platform, etc. This allows determining the real height of the person.

To determine the real height of the person, the following notations are made: h = individual's real height; l = length of the shadow; A = solar altitude in degrees; δ = solar declination in degrees; ϕ = terrestrial latitude in degrees; n = Julian date; Az = solar azimuth in degrees measured clockwise from north; t = time from solar noon, in hours (e.g. t=5 for 5pm); ω = angular velocity of the earth's rotation, ω = 2π rad/hr.

The height as a function of the shadow length is

$$h = l\frac{sin(A+M)}{cosA} \quad (1)$$

where M is degrees of the ground. Solar altitude is thus given by $sinA = sin\phi sin\delta + cos\phi cos\delta cos(wt)$.

The preliminary experiments in the following did not have yet implemented the light source compensation step. Thus, the imagery contains a timestamp (in the angle of the shadow) associated with each individual, thus which is in itself a marker of an individual. However, five subjects in the database were recorded at approximately the same time, so we consider captured images may not contain timestamp.

3.3. Extraction of shadow features

After extracting image sequences of shadow silhouettes of one gait cycle, which is used to partition the sequences, dynamic features of gait sequence are obtained as follows: in each row of the image $I(x, y, t)$ the largest distance $H(y, t)$, which we refer here as "gait stripe", is determined as the absolute value of the distance between extremities of this shape, illustrated in Fig. 4 (a) as a horizontal stripe measured from left to right.

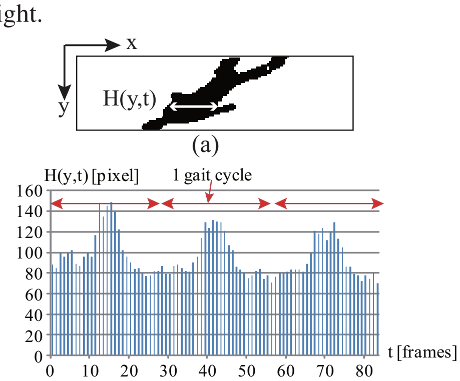


Fig. 4. (a) Determination of $H(y, t)$, (b) An example of gait stripes ($H(y, t)$).

3.4. Frequency analysis and classification

Since the gait motion repeats in time, the gait stripe $H(y, t)$ is also repetitive as shown in Fig. 4 (b). We decided to apply spherical harmonics transforms [4] because of its robustness to noise. Spherical harmonic transforms are essentially Fourier transforms on the sphere. Spherical harmonic functions $\{Y_l^m(\theta, \phi) : |m| \le l \in \boldsymbol{N}\}$ are special functions defined on the unit sphere $\boldsymbol{S^2}$ [4] as:

$$Y_l^m(\theta,\phi) = \begin{cases} \sqrt{2}K_l^m cos(m\phi)P_l^m(cos\theta) & m > 0 \\ \sqrt{2}K_l^0 P_l^0(cos\theta) & m = 0 \\ \sqrt{2}K_l^m sin(-m\phi)P_l^{-m}(cos\theta) & m < 0 \end{cases} \quad (2)$$

where $\theta \in [0, \pi]$, $\phi \in [0, 2\pi]$, K_l^m is a scaling factor defined $K_l^m = \sqrt{\frac{(2l+1)}{4\pi}\frac{(l-|m|)!}{(l+|m|)!}}$, and P_l^m is the associated Legendre polynomial. The spherical harmonic functions are projected into spherical harmonic coefficients c_l^m as follows:

$$c_l^m = \int_S f(\theta,\phi)Y_l^m(\theta,\phi)ds. \quad (3)$$

Here, f is an original function.

For characterizing gait stripes, we obtain spherical harmonic coefficients of gait stripes $H(y, t)$ as features. To obtain spherical harmonic coefficients c_l^m of $H(y, t)$, we define the original function $f(\theta, \phi)$ as $f(\theta, \phi) = H(y, t)$ where $\theta = \frac{t}{T} \times \pi, \phi = \frac{y}{Y} \times 2\pi$. Here, T is the number of frames in one gait cycle and Y represents the height of images. The total number of coefficients are l^2.

Although the extracted target region of the silhouette image may include noise, by using the spherical harmonics, features of each person can be obtained robustly against noise. In the proposed method, we extract spherical harmonic coefficients from gait stripes at first, and the classifier is trained by using training data sets. Then in the identification phase, the same spherical harmonic coefficients are extracted from gait stripes of test data sets, and the subject is identified by the classifier.

4. EXPERIMENTS

In this section, firstly we show experimental results of gait recognition with gait silhouettes after applying the described methodology. Next, we explore the degradation in classification with the reduction in spatial and temporal resolution of the images, which allows us to tailor an observational platform to the needed/sufficient classification rate. Then, we used body silhouettes for gait recognition to show that the shadow could have gait information as much as body. Finally, we compared the proposed method with conventional methods.

In our experiments, one gait cycle is determined manually, and the image was scaled to a uniform height, set to 100 pixels, and aligned with respect to its horizontal centroid. Moreover, we used 5 subjects walking in the direction from point 2 to point 3 (Fig. 2 (a)), and the database contains 20 raw image sequences, which contain 5 different subjects with 4 sequences for every subject. As the classifier, the k-nearest neighbor classification was applied to the spherical harmonic coefficients. We used the leave-one-out cross validation to estimate the classification error rate.

4.1. Shadow only, full spatio-temporal resolution

In the first experiment, we used coefficients c_l^m of gait stripes H for classification. The number of features of each person depends on the order l of spherical harmonic functions. Fig. 5 represents the correct classification rate (CCR) with respect to order of coefficients. The CCR exceeded 95.0 % for more than 49 coefficients (l=7), so in the following experiments, we used 49 coefficients.

4.2. Shadow only, reduced spatio-temporal resolution

We changed the resolution both spatially and temporally for aerial based images. The classifier is trained by using the training data sets of full resolution. For the test data sets, we decreased the spatial and temporal resolution to quarter and half, respectively. Table 1 shows the result of classification. The CCR at half spatial and half temporal resolution shows 75.0 %.

4.3. Recognition from body silhouette only, and comparison in classifications from body only and shadow only

We used body silhouettes and changed the resolution both spatially and temporally by the same procedure with the second experiment. Table 2 shows the result of classification. Almost all results of body silhouettes are the same with shadow silhouettes, and we could say that the shadow has as much information as the body.

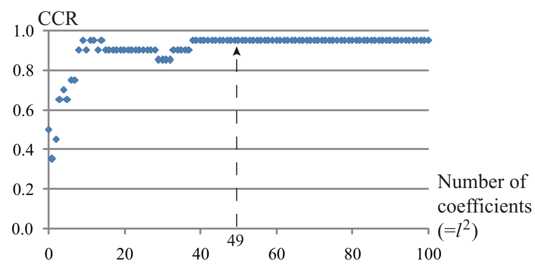


Fig. 5. CCR [%] with respect to the order of the spherical harmonic coefficients.

Table 1. CCR [%] of shadow silhouettes with respect to spatial and temporal resolution. T is the number of frames in one gait cycle.

	Image size (width, height)		
	(400, 100)	(200, 50)	(100, 25)
T [frames]	95.0	75.0	50.0
$T/2$ [frames]	85.0	75.0	35.0
$T/4$ [frames]	55.0	55.0	30.0

Table 2. CCR [%] of body silhouettes with respect to spatial and temporal resolution.

	Image size (width, height)		
	(400, 100)	(200, 50)	(100, 25)
T [frames]	95.0	70.0	45.0
$T/2$ [frames]	80.0	75.0	35.0
$T/4$ [frames]	35.0	35.0	20.0

4.4. Comparison of the proposed method and conventional methods

In the final experiment, we compared the proposed method with two conventional methods; Fourier transform-based method (DFT) [5] and affine moment invariants-based method (AMIs) [6]. These two methods achieved high performances on the SOTON database. We applied these two methods to the shadow gait database, and Table 3 shows the comparison of their experiments and our experiment. From these results, our method achieved the highest CCR.

Table 3. Comparison of the proposed method and conventional methods.

	DFT [5]	AMIs [6]	The proposed method
The number of features	10800	6	49
CCR [%]	85	70	95

5. CONCLUSION

This paper presented a methodology for shadow biometrics and demonstrated gait recognition from shadow analysis. Shadows were extracted by segmentation from image sequences from a gait database with both shadows and bodies visible. Shadow silhouettes were scaled to the same height and a set of silhouette stripes were determined, for which the length was determined in each image. A more comprehensive method, which compensates for variability in observation conditions was outlined. Spherical harmonics were applied to the stripes for each gait sequence, followed by a k-nearest neighbor classification to spherical harmonic coefficients. A correct classification rate (CCR) of 95.0 % from 49 coefficients was obtained. A reduction of resolution to 50 % (from 1 to 2cm per pixel) reduced the CCR from 95.0 % to 75.0 %. Two near term directions of work are: (1) implement the equations that provide a corrective scaling with different positions of the sun, (2) study the robustness to changed direction of walk.

6. REFERENCES

[1] A. Stoica, *Towards Recognition of Humans and their behaviors from Space and Airborne Platforms: Extracting the Information in the Dynamics of Human Shadows*, Proc. the 2008 Bio-inspired, Learning and Intelligent Systems for Security, pp.125-128, 2008.

[2] M. S. Nixon, T. N. Tan, and R. Chellappar, *Human Identification Based on Gait*, Springer-Verlag New York, Inc. Secaucus, NJ, USA, 2006.

[3] T. Tanaka, A. Shimada, D. Arita, and R. Taniguchi, *Object Detection under Varying Illumination based on Adaptive Background Modeling Considering Spatial Locality*, Proc. the Third Pacific-Rim Symposium on Image and Video Technology, pp.645-656, 2009.

[4] R. Green, *Spherical Harmonic Lighting: The Gritty Details*, SCEA Research and Development, 2003.

[5] K. Sugiura, Y. Makihara, and Y. Yagi, *Gait Identification based on Multi-view Observations using Omnidirectional Camera*, Proc. 8th Asian Conference on Computer Vision, pp.452-461, 2007.

[6] Y. Iwashita and R. Kurazume, *Person identification from human walking sequences using affine moment invariants*, Proc. IEEE Int. Conf. Robotics and Automation, pp.436-441, 2009.