FRONTAL VIEW-BASED GAIT IDENTIFICATION USING LARGEST LYAPUNOV EXPONENTS

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ABSTRACT

This paper features two novel approaches to gait recognition; one is frontal motion analysis, using a single camera. This allows the use of other biometrics easily. Second is analysing gait using of nonlinear dynamics of time series, normally used in chaos theory, for classification.

A set of point light sources attached to various points of a walking person allows the walker to be identified. Phase-space analysis of trajectories of these Moving Light Displays (MLDs) provides sufficient information for identification of people by their gait. Using chaotic measures to identify humans by their gait sets a significant precedent.

1. INTRODUCTION

Gait as a biometric, has desirable properties. It is capable of being used at long distances, is non-intrusive, non-invasive, and is hard to disguise. It can also be combined with other biometrics like face features[1][2][3] to give a more robustidentification process.

In the main, current gait recognition approaches analyse walking which proceeds in a plane parallel to a camera, the so-called fronto-parallel (FP) view. This gives the largest variation in silhouette from which the time series data is obtained for analysis. From a far distance, this is advantageous. However a clear field of view is needed and this requires a large uncluttered area.

Motion from a plane perpendicular to this, the fronto-normal view (FN), is considered as a special case. But very commonly, people are made to queue up to access a facility. In a corridor like structure, we assume that a subject will be approaching a camera. In such situations gait is used as a supporting biometric because as the subject draws nearer, other biometrics such as face or iris can be used for robust recognition. In summary, the advantages of the FN view are:

i) Single camera deployment.
ii) Ease of combining other biometrics.
iii) Smaller physical space needed.

This approach has its own unique challenges when fast and reliable recognition is necessary.

Johansson's[4] experiments with Moving Light Displays (MLD) did notshowed that without the use of the body silhouette, and when walking, the cadence and position of the MLDs allowed for identification of the subject as a human.

A recent survey on gait[5] divided up the main approaches on gait into model based and model free.

Model free approaches look for changing features in the video frames without considering the object. In the Model based approaches assume that the image of the 3D human is projected onto a 2D image. This constrains the type of motion and allows us to find the parameters for the type of movement. In this way, the movement of body part may be dynamically analysed.

Phase space

The motion of the MLDs create a time series of point coordinates. In doing so, we may create a phase space and use the appropriate methods to analyze the motion. However, much of the work in this area, as applied to human action analysis, focuses on motion recognition. Thus they do not attempt to distinguish motion *between* individuals, but rather identify a motion *among* several for an individual.

In the work by Campbell and Bobick[6], phase space is employed to characterize body movements using a matching criterion to identify the motion. Moeslund and Granum[7] use an Analysis-by-Synthesis approach, employing phase space to describe the motion of the model. This space is reduced by kinematics and geometric constraints corresponding to movement and placement of the body parts.

Chaotic biological movement

Van Emmerik et al[8] in a tutorial overview, discuss how various seemingly simple human actions are the result of the interaction of complex systems. West and Scafetta[9] analyze the stride length of humans which have been shown to be slightly multifractal which can be modelled using nonlinear oscillators. Dingwell and Cusumano[10] attempt to quantify local dynamic stability of human walking to identify subjects who were prone to falling. This was done using chaotic measures.

The concept of phase-space analysis of chaotic systems is extended here to enable joint analysis of a number of motion trajectories at the same time. The trajectories specify motion of a number of MLDs during a short distance walk. We can thus characterize their behaviour in a compact way.

2. INITIAL TRACKING EXPERIMENTS

In frontal gait recognition, we use feature points that have more motion in the image plane. This would be the hands, feet and knees, for a FP walk. For a FN walk this is also true, although the motions are smaller in magnitude. We set up the coloured markers as shown in Fig. 1, for the two kinds of walk.

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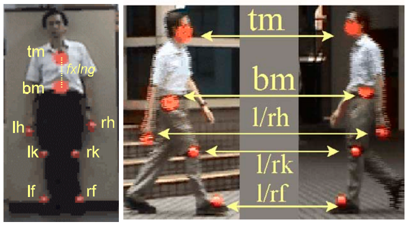

Fig. 1. Marker designations

The designations are as follows:

Left/Right HAND	Left/Right FOOT	Left/Right KNEE
lh/rh	lf/rf	lk/rk

Two additional discs of the same colour are attached at the waist and neck level. They are used for distance normalization, due to the looming effect of a FN walk. They are:

Top/Bottom MARKER - tm/bm

The markers are tracked using the CAMSHIFT[11] algorithm. We take video clips of twelve subjects and a further three for testing. The unnormalized and normalized plots are shown in Fig.2 and Fig. 3.

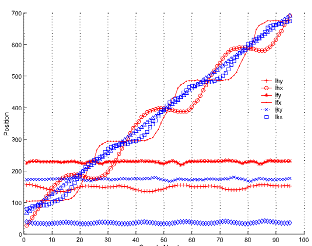

Fig. 2. Unnormalized FP walk data

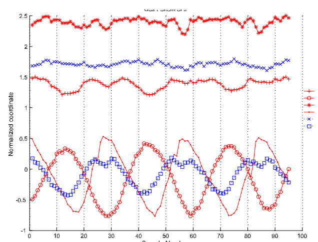

Fig. 3. Normalized FP walk data

Next, the autocorrelation plot in Fig. 4 shows the strong periodicity in movement, especially in the x-axis which swamps out the “non-periodic” signal in the y-axis.

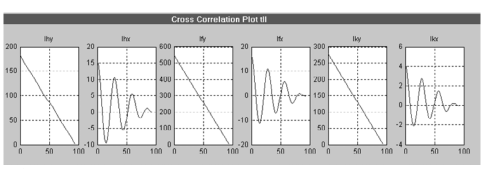

Fig. 4. Autocorrelation plot of left marker trajectories - FP Left to Right

For a FN walk, the unnormalized and normalized trajectories are shown in Fig. 5 and Fig. 6

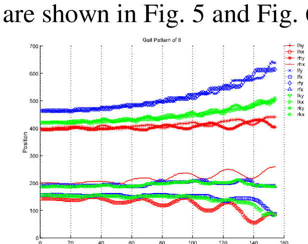

Fig. 5. Unnormalized FN walk data

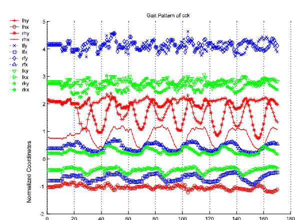

Fig. 6. Normalized FN walk data

In contrast, the autocorrelation plot for FN gait does not show any periodicity in *any* of the twelve marker trajectories. This is an indicator of nonlinear dynamics or chaotic behaviour.

3. DYNAMICAL ANALYSIS

To test for chaotic behaviour, the *scalar* time series is subjected to dynamical analysis which assumes that the time series data X is generated by a vector valued process. The actual state vectors describing this process may never be known. But we can create a set of *phase space* vectors which are topographically equivalent, and can be considered to be a reconstruction of them. Takens[12] "method of delays" is an established method for doing this. He also shows that if the dimension of the phase space vectors m is larger than the dimension of the *chaotic* attractor D, we can say that the phase vectors *embed* the state vectors and,

$$m > 2D + 1 \quad (1)$$

Thus the reconstructed trajectory of X is made up of several phase space vectors as follows:

$X = [X_1\ X_2 \ldots X_m]^T$ where X_i is the state of the system at sample i.

Each row of X is a phase-space vector with a length of the embedding dimension m. That is, for each X_i,

$X_i = [\ x_i\ x_{i+\tau} \ldots\ x_{i+(m-1)\tau}\ ]$ where τ is the time lag.

This being for a time series $x = \{x_1, x_2, \ldots, x_N\}$ with N points. So X is a M by m matrix, and we have M the number of phase space vectors being $N - (m - 1)\tau$.

There are several ways to determine the parameters m and τ. For τ, the standard method is to take the time when the autocorrelation plot first goes to zero. But we see that it never reaches zero, so we use the time delayed mutual information measure as proposed by Fraser and Swinney[13]. A sample plot is shown in Fig. 7 for one person

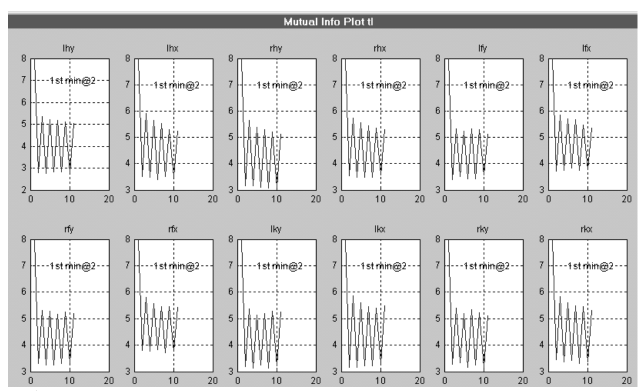

Fig. 7. Mutual Information - all markers for a person - FN

The point at which the first minimum of the plot is taken to be the best value for τ which is 2, in this case, for all twelve marker trajectories.

For m, we use the method of false nearest neighbours (FNN) as proposed by Kennel et al[14] and shown in Fig.8.

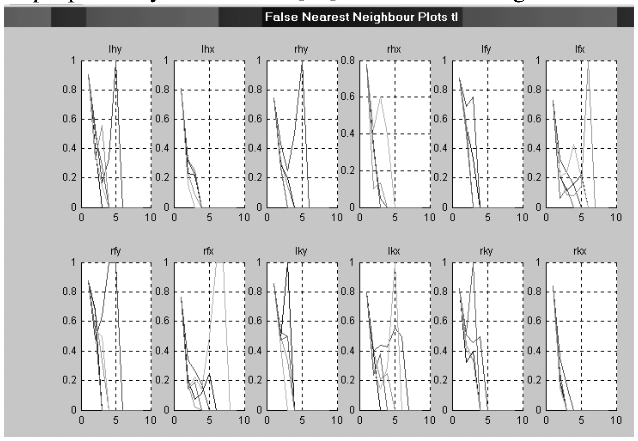

Fig. 8. False Nearest Neighbour plot

We find the smallest value to be six. This is for all twelve trajectories belonging to all twelve subjects.

4. MEASURING CHAOS WITH LYAPUNOV EXPONENTS

There are several measures of chaotic behaviour, the largest Lyapunov exponent λ_1 being the most useful and commonly used. If the system equations generating the data is known, it is quite straightforward to calculate it.

It describes how quickly trajectories approach or come together, given different initial conditions. This comes directly from a definition of chaos. Let the Euclidean distance between them be d. Then λ_1 is the mean exponential rate of divergence of two initially close orbits from an initial time t_0 to t_R, :

$$\lambda_1 = \frac{1}{t_R - t_0} \sum_{i=1}^{R} \log_2 \frac{d(t_i)}{d(t_{i-1})} \qquad (2)$$

One of the more recent methods to calculate λ_1 is by Rosenstein[15] and independently, by Kantz[16]. This method is suitable for small and noisy data sets.

From the above, we assume a fixed samping time period Δt and sample number i, so that t_R-t_0 = $i\Delta t$. Taking logarithms on both sides of (3), we have:

$$d(t) = C_j \exp \lambda_1 (i\Delta t) \qquad (3)$$

where C is a constant. Alternatively, from (3), for each time point i,

$$\log_2 d(t_i) \; = \; \lambda_1 i\Delta t + \log_2 d(t_{i-1}) \qquad (4)$$

Which are a set of approximately parallel lines for i = 1 to M. Thus we can find the largest Lyapunov exponent by fitting a line using Least Squares to the average line:

$$y(i) = \frac{1}{\Delta t} \frac{1}{N_j} \sum_j \ln \; d_j(i) \qquad (5)$$

where d_j is the distance between the j^{th} set of points. This is done for all N_j which are the number of points.

This averaging process cycles through *all* the available data points and will also reduce the effect of noise in the data.

Fig. 9 is a plot for the twelve marker trajectories of a person.

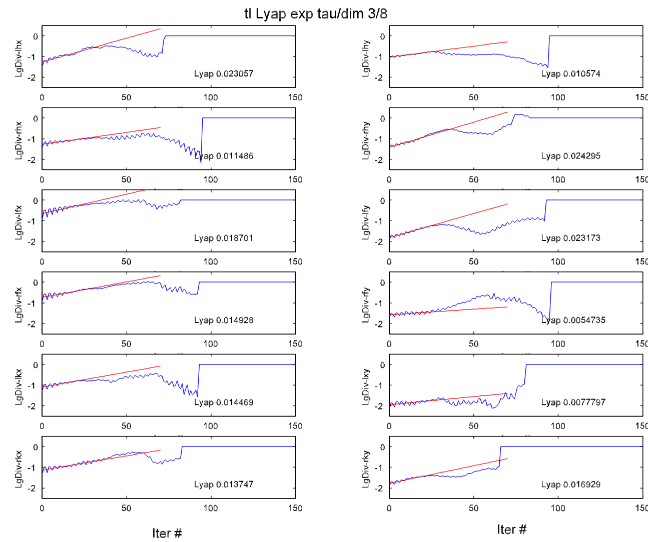

Fig. 9. Largest Lyapunov Exponents: Rosenstein's method

We see that the data is mildly chaotic as λ_1 is positive.

5. RESULTS

A table of λ_1 values is generated for all videos of the twelve subjects and the three test videos. Because of the limited page size, we show the table for three subjects *and* a second video taken of them a few minutes later. These are *gjh/gjh1*, *ht/ht1* and *tl/tl1*. The suffix '1' denotes the second video.

TABLE 1 λ_1 VALUES

τ2m5	gjh	gjh1	ht	ht1	tl	tl1
lhx	1.801	3.710	1.781	2.073	2.242	2.026
lhy	3.726	4.853	2.506	3.572	2.614	1.770
rhx	3.629	2.633	4.016	3.811	2.975	2.582
rhy	3.869	3.333	4.431	3.027	2.962	2.230
lfx	2.495	2.332	2.347	2.112	1.535	1.760
lfy	2.745	1.740	2.256	2.864	2.233	2.219
rfx	2.280	3.145	2.391	2.185	1.985	2.024
rfy	2.832	3.352	3.680	4.267	1.103	3.181
lkx	2.710	2.490	1.988	1.882	2.308	1.644
lxy	4.088	2.641	1.888	2.472	1.912	2.450
rkx	3.395	3.361	2.505	2.173	1.561	1.293
rky	2.877	3.361	3.168	2.538	1.605	2.453
avg	3.037	3.079	2.746	2.748	2.086	2.136
var	0.67	0.76	0.84	0.74	0.56	0.48

A significant observation here is that the average $\overline{\lambda}_1$, of all the λ_1 for a person is relatively constant for the three subjects *gjh*, *ht* and *tl*. To test this out, we vary τ and m and for each subject and calculate the average of the differences $\delta\overline{\lambda}_1$ between each *pair* of subjects.

TABLE 2 λ_1 VALUES FOR VARIOUS τ,m

	gjh	gjh1	ht	ht1	tl	tl1	$\delta\lambda_1$
T2m5	0.04		0.00		0.05		**0.03**
avg	3.04	3.08	2.75	2.75	2.09	2.14	
T2m6	0.01		0.07		0.15		**0.11**
avg	2.98	2.99	2.64	2.57	1.86	2.01	
T2m7	0.04		0.07		0.06		**0.07**
avg	2.91	2.87	2.50	2.42	1.75	1.82	
T2m8	0.03		0.15		0.09		**0.12**
avg	2.72	2.75	2.32	2.17	1.61	1.70	
T3m5	0.04		0.03		0.07		**0.05**
avg	2.80	2.76	2.32	2.35	1.74	1.81	
T3m6	0.10		0.10		0.78		**0.44**
avg	3.12	3.02	2.65	2.55	2.04	2.83	
T3m7	0.12		0.11		0.11		**0.11**
avg	2.41	2.30	1.76	1.65	1.17	1.28	
T3m8	0.14		0.13		0.21		**0.17**
avg	2.10	1.96	1.46	1.32	0.84	1.05	
T4m6	0.02		0.01		0.18		**0.10**
avg	2.10	2.09	1.36	1.35	0.94	1.12	
T4m7	0.03		0.24		0.25		**0.24**
avg	1.67	1.69	1.12	0.88	0.59	0.84	
T4m8	0.15		0.22		0.28		**0.25**
avg	1.31	1.47	0.89	0.66	0.35	0.63	

We want the differences to be as small as possible, which is true for τ=2 and m=5, which is close to 6. Thus we receive independent confirmation that the parameter values are valid.

We see that by measuring chaos in gait, we can characterize a person's walk. Now, other people can have similar values of $\bar{\lambda}_1$ .The following confusion matrix shows this.

TABLE 3 CONFUSION MATRIX

PREDICTED/ACTUAL in %												
	cck	gjh	ht	jl	lal	ma	ohl	ry	st	tl	wkc	wwy
cck	100											
gjh		50									50	
ht			100									
jl				33		33	33					
lal					100							
ma				33		33	33					
ohl				33		33	33					
ry								50				50
st									100			
tl										100		
wkc		50									50	
wwy								50				50
$\bar{\lambda}_1$	2.58	3.04	2.75	2.32	2.41	2.34	2.31	2.67	2.87	2.09	3.03	2.69

A useful partitioning of subjects has been achieved. The use of $\bar{\lambda}_1$ shows promise as a feature for classification. This paves the way for future work in this direction.

6. CONCLUSIONS

Clinical studies on gait show that it is chaotic in nature. Current approaches using the fronto-parallel view in the analysis of motion does not capture this fact, but indicate that the movement is grossly periodic.

The experiments we performed demonstrate that fronto-normal view shows chaotic motion more clearly and allows us to use the Largest Lyapunov Exponents to characterize gait. This is a very important result which says that the significant information for gait recognition lies within the chaotic behaviour of the motion trajectories rather than the cyclostationary parts. Future work will require a larger database of subjects and markerless tracking. There will also be a need to see if other combinations of λ_1 or with other biometrics are useful as well.

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