# CHAOTIC CHARACTERISATION OF FRONTAL NORMAL GAIT FOR HUMAN IDENTIFICATION

*Tracey K. M. Lee, 1M. Belkhatir, 2P.A. Lee, †Saeid Sanei and 3K. F. Loe

*School of EEE Singapore Polytechnic 500 Dover Road, S(139651) tlee@sp.edu.sg
1,2,3School of IT, Monash University Malaysia, 2 Jln Kolej, Bandar Sunway, 46150 Petaling Jaya
1mohammed.belkhatir@infotech.monash.my, 2lee.poh.aun@infotech.monash.my, 3loe.kia.fock@infotech.monash.my
†Centre of Digital Signal Processing, Cardiff University, Cardiff, CF24 3AA.saneis@cf.ac.uk

## ABSTRACT

*Human recognition using gait features in predominantly frontal-normal motion has been described in this paper.Compared to current methods for gait identification, this allows convenient combination of other biometrics using a single camera. We analyse how this motion yields more dynamic information, allowing us to characterise gait in a new way, using nonlinear dynamics of time series normally used in chaos theory. Using chaotic measures to identify humans by their gait is a significant precedent.*

*Phase-space analysis of trajectories of a set of Moving Light Displays (MLDs) provides sufficient information for identification of people by their gait.*

*A number of experiments has been set up to demonstrate the viability of this approach which contribute to the relatively unexplored area of fusion of face with gait. This provides a more robust identification scheme.*

## 1. INTRODUCTION

We use our five senses to recognize objects around us. Our senses cannot directly detect time but *time*, as part of motion, brings an extra dimension to recognition. In Johansson's [1] experiments, a set of lights attached to a human in a dark room has no meaning by itself when stationary. However when these lights move due to human movement, they are easily identified as a human walking, by virtue of the cadence and position of these Moving Light Display (MLDs).

Today's widespread availability of low cost web cameras (webcams) allows us to easily use spatial information with a temporal dimension for various computing tasks in recognition. It is natural to use other biometrics which exist in the video - for example face features, to improve recognition rates.

### 1.1 Gait History

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. A recent survey on gait[2] 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.

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[3], phase space is employed to characterize body movements using a matching criterion to identify the motion. Moeslund and Granum[4] 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.

### 1.2 Chaotic biological movement

Attempts at describing human activity described by ECG and EEG signals show that these signals only have the appearance of periodicity. Recent attempts at analysing these signals use various nonlinear techniques. One method is that of using deterministic chaos. One view of chaos is that some seemingly simple motion is the result of the interaction of complex systems. This was described by Van Emmerik et al.[5] in a tutorial overview. West and Scafetta[6] analyze the stride length of humans which have been shown to be slightly multifractal which can be modelled using nonlinear oscillators. Dingwell and Cusumano[7] 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.

### 1.3 Other common biometrics

Face Recognition (FR) technology is a relatively mature field. The FERET methodology[8] is an attempt to standardize the rating of FR algorithms. It supplies a standard set of faces taken under fairly unconstrained conditions. It also provides a baseline PCA algorithm. We will use PCA based technology for Face detection and recognition as a vehicle to demonstrate the usefulness of frontal normal gait. In our system, we use the measure of gait to simply preselect suitable candidates for face recognition.

## 2. ANALYTICAL REVIEW OF PRIOR WORK

In this section, we present the three main motivations for FN gait analyses.

### 2.1 Space constraints

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. 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.

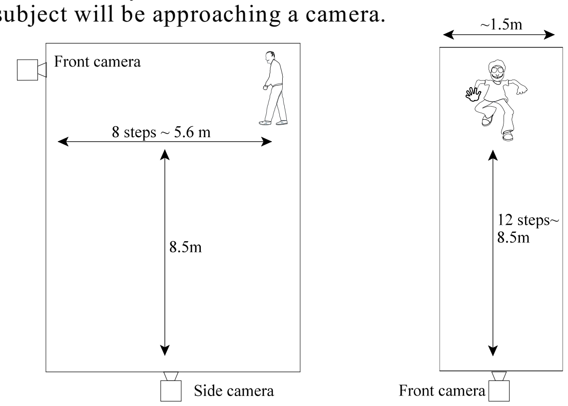


Fig. 1. FP vs FP - dimensions

Depending on the type of analysis need, in a FP walk, at least two cycles or four steps are needed. For more robust estimation of the period of walking, twice that distance is needed. This translates to the need to adequately capture enough walking cycles. For example, if a person were to walk about 0.7 m per step, to apture a movement of 8 steps would be about 5.6 m. However because of the focal length of the camera, the camera distance required to capture this movement is about 8.5 m. Practically, it is difficult to have such a wide uncluttered space, when we desire to measure a person's gait as many people and objects will be present.

In a FN walk, we can still use the 8.5 meters, but this time, we cover twelve steps and we only need a corridor-like structure, the width being about that of a human body. A considerable amount of space is saved. This is illustrated in Fig 1.

### 2.2 Combination of biometrics

Several combinations of biometrics have been tried. For example, face and speech, face and iris and so on. Face with gait has been relatively unexplored, and these have used mainly the FP approach[9][10]. However, in using this approach, Zhou and Bhanu[11] use a *profile* view of a face with gait in order to use one camera at 3.3 m from the subject. The work by Bazin[12] includes the ear and footfall as biometrics. In most cases, two cameras are needed. The problems of alignment and synchronisation are significant. Single camera or monocular capture of video is preferred even if less data is obtained.

Table 1 Table of the types of biometric combinations possible with the two views of gait in a monocular set up

| Biometric | FP (side view) | FN |
|---|---|---|
| Face | Not reliable | Frontal - well researched |
| Gait | Good segmentation strong periodicity | Difficult to process Can use nonlinear |
| Iris | Not possible | Near distance use |
| Ear | Not sure of usefulness | dubious use |

From Table 1, we see that the FN view allows one to use face and iris together with gait for a robust recognition system. But the FN view is challenging, having to compensate for the looming effect.

### 2.3 Use of nonlinear analyses for gait

In fronto-parallel movement, the motions of the arms and feet are described by articulated joints which undergo sinusoidal motion. Thus we use such terms as pendulums and cycloids to describe motion. Model based FP gait analyses attempt to derive periodic information from these motions.

Model free approaches use the silhouette of a walker. As we can see later, the periodic component is dominant. In fact, the only other kind of temporal analyses have been of the AutoRegressive (AR) type as done by Veeraghavan et al. [13] Nonperiodic analyses are capable of giving new insights into temporal data. In summary, the advantages of the monocular FN non-silhouette approach are:

i) Smaller physical space needed.
ii) Ease of combining other biometrics.
iii) Non-periodic motion analysis

## 3. INITIAL TRACKING EXPERIMENTS

In FN 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. For the two kinds of walk, the coloured marker set up is shown in Fig. 2.

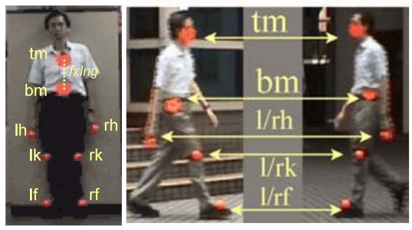


Fig. 2. Marker designations

The marker designations are: *lh/rh* - left/right hand, *lf/rf* - left/right foot, and *lk/rk* - left/right knee. There are two additional discs of the same colour which are attached to the waist and neck. They are used for distance normalization, due to the looming effect of a FN walk. They are: *tm/bm*, the top/bottom markers. The markers are tracked using the CAMSHIFT[14] algorithm. The normalized plots for FP and FN walks are shown in Fig. 3 and Fig. 4 respectively.

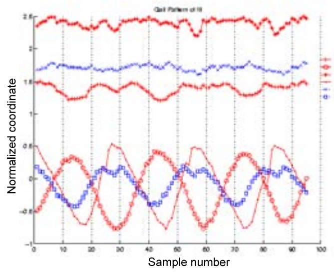


Fig. 3. Plot of normalized FP walk

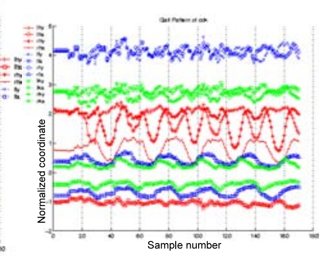


Fig. 4. Plot of normalized FN walk

Next, the autocorrelation plot in Fig. 5 shows the strong periodicity in movement, especially in the x-axis which swamps out the "non-periodic" signal in the y-axis.

In contrast, the autocorrelation plot for FN gait in Fig. 6 does not show any periodicity in *any* of the twelve marker trajectories. This is an indicator of nonlinear dynamics or chaotic behaviour. However, it is interesting to note that the motion of a FN walk *silhouette* is periodic[15].

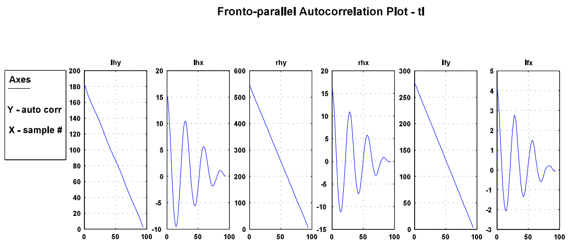


Fig. 5. Autocorrelation plots of left marker trajectories - FP Left to Right

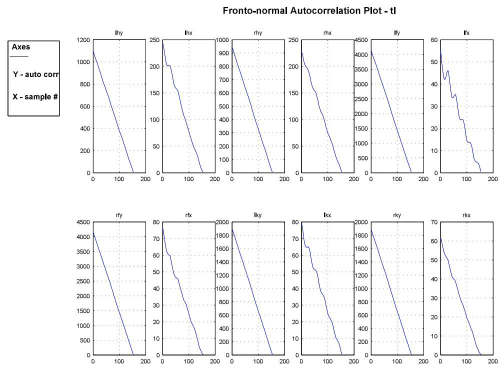


Fig. 6. Autocorrelation plot - Fronto-Normal (FN) walk

# 4. CHAOS MEASUREMENT

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[16] "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,

$$m > 2D + 1$$

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 $\tau$ 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 $\tau$. For $\tau$, the standard method is to take the time when the autocorrelation plot first goes to zero. But we see that it never reaches zero until the end of the walk, so we use the time delayed mutual information measure as proposed by Fraser and Swinney[17]. A sample plot is shown in Fig. 7 for one person.

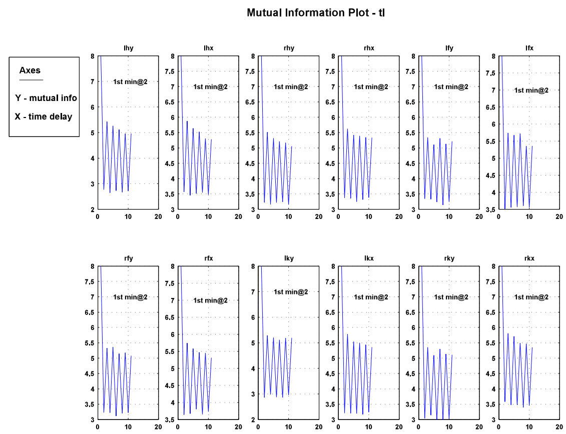


Fig. 7. Mutual Information plots for the markers of one person in a FN walk

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

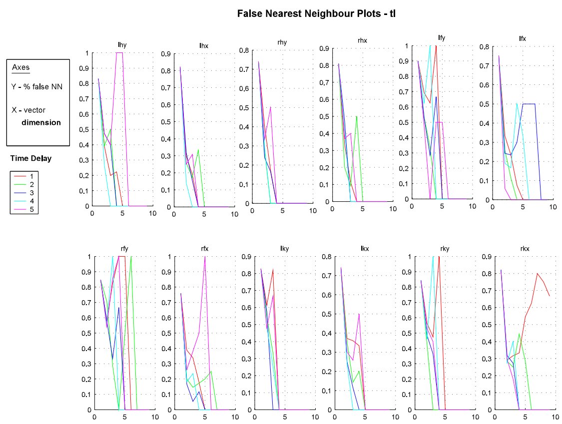


Fig. 8. False Nearest Neighbour plots for the markers of one person in a FN walk

For $m$, we use the method of false nearest neighbours (FNN) as proposed by Kennel et al[18] and shown in Fig.8. Taking the average of *all* the largest values where the FNN goes to zero, we find the nearest integer value to be six.

# 5. MEASURING CHAOS WITH LYAPUNOV EXPONENTS

There are several measures of chaotic behaviour, the largest Lyapunov exponent $\lambda_1$ 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. Then $\lambda_1$ is the mean exponential rate of divergence of two initially close orbits from an initial time $t_0$ to $t_i$, The divergence $d_j$ between the $j^{th}$ set of points on the two orbits is the Euclidean distance between them.

$$\lambda_1 = \frac{1}{t_i - t_0} \sum_{k=1}^{i} \log_2 \frac{d(t_k)}{d(t_{k-1})}$$

One of the more recent methods to calculate $\lambda_1$ was formulated by Rosenstein[19] and independently, by

Kantz[20]. This method is suitable for small and noisy data sets. Assume a fixed samping time period $\Delta t$ and that at $t_i$ the sample number is $i$ so that $t_i - t_0 = i\Delta t$. We substitute the subscripted time $t_i$ by its index $i$. Taking logarithms on both sides of eqn.(1) , we have:

$$\log_2 d_j(i) \;=\; \lambda_1 i\Delta t + \log_2 d_j(0) \qquad (1)$$

The initial separation $\log_2 d_j(0)$ is constant, so we have a group of $j = 1$ to $M$ (phase space vectors) approximately parallel lines for the sample number $i$. The main feature of this method is that we average the $\log_2 d_j(i)$ values for all $j$ pairs of sample point at each sample $j$. Then

$$\langle \log_2 d_j(i)\rangle\ /\Delta t \;=\; \lambda_1 i \;+\; \langle \log_2 d_j(0)\rangle\ /\Delta t \qquad (2)$$

where <·> is average operator. We average further by fitting a line using Least Squares to the "average line" of eqn. (2). shown as the straight lines in Fig 9. Then $\lambda_1$ is the slope of the

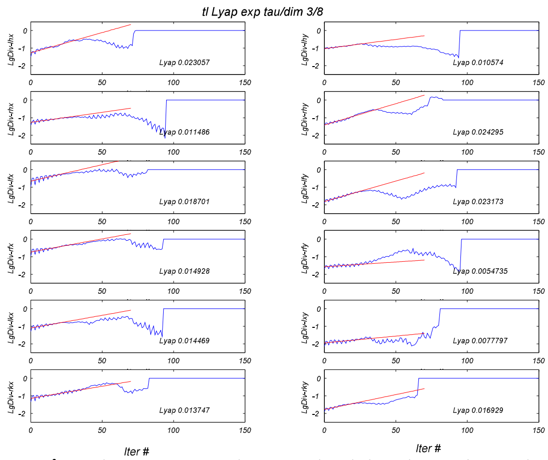


Fig. 9. $\lambda_1$ using Rosenstein's method for the trajectories of the markers for a person

fitted lines. Fig. 9 is a plot for the twelve marker trajectories of a person.We see that the data is mildly chaotic as $\lambda_1$ is positive.

## 6. RESULTS

We have videos of twelve subjects and we generate the table of $\lambda_1$ values for them. Another set is generated for three of the twelve subjects. 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 *s02/s02a*, *s03/s03a* and *s10/s10a*. The suffix 'a' denotes the second video.

Table 2 $\lambda_1$ VALUES

| τ2m5 | s02 | s02a | s03 | s03a | s10 | s10a |
|---|---|---|---|---|---|---|
| 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 $\bar{\lambda}_1$, of all the $\lambda_1$ for a person is relatively constant for the three subjects *s02*, *s03* and *s10*. To test this out, we vary $\tau$ and $m$ and for each subject and calculate the average of the differences $\delta\bar{\lambda}_1$ between each *pair* of subjects.

Table 3 $\lambda_1$ values for various $\tau$,m

| | s02 | s02 | s03 | s03a | s10 | s10a | $\delta\bar{\lambda}_1$ |
|---|---|---|---|---|---|---|---|
| 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 $\tau$=2 and $m$=5, which is close to 6. Thus we receive 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 $\bar{\lambda}_1$. We assume a normal distribution and use a pooled covariance to compute the Bhattacharyya distance between two classes *i, j* as a measure of statistical separability.

$$B_{ij}=(1/8)(\mu_i-\mu_j)^T((\Sigma_i+\Sigma_j)/2)^{-1}(\mu_i-\mu_j) \qquad (3)$$
$$+(1/2)\ \ln(|(\Sigma_i+\Sigma_j)/2|/(|\Sigma_i|^{1/2}|\Sigma_j|^{1/2})$$

Table 4 Bhattacharyya Distance between classes

| | *s01* | *s02* | *s03* | *s04* | *s05* | *s06* | *s07* | *s08* | *s09* | *s10* | *s11* | *s12* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *s01* | 0 | 85 | 11 | 25 | 11 | 22 | 27 | 3 | 31 | 78 | 75 | 5 |
| *s02* | | 0 | 36 | 201 | 155 | 190 | 206 | 56 | 14 | 324 | 1 | 51 |
| *s03* | | | 0 | 68 | 43 | 62 | 71 | 3 | 6 | 146 | 29 | 2 |
| *s04* | | | | 0 | 3 | 1 | 1 | 45 | 111 | 15 | 185 | 51 |
| *s05* | | | | | 0 | 2 | 4 | 2 | 2 | 2 | 141 | 29 |
| *s06* | | | | | | 0 | 1 | 103 | 18 | 175 | 2 | 45 |
| *s07* | | | | | | | 0 | 48 | 115 | 14 | 190 | 53 |
| *s08* | | | | | | | | 0 | 15 | 111 | 48 | 1 |
| *s09* | | | | | | | | | 0 | 206 | 10 | 12 |
| *s10* | | | | | | | | | | 0 | 303 | 119 |
| *s11* | | | | | | | | | | | 0 | 43 |
| *s12* | | | | | | | | | | | | 0 |

By selecting the distances less than or equal to 1 to denote classes being inseparable, we have the confusion matrix in Table 5. This shows that *s04, s06, s07* should be in one group, another in *s02, s11* and then *s08,s12*.

For our final experiment, we assume that the computed value of $\bar{\lambda}_1$ preselects the group comprising *s04, s06, s07*.

Table 5 Confusion Matrix

PREDICTED/ACTUAL in %

| | s01 | s02 | s03 | s04 | s05 | s06 | s07 | s08 | s09 | s10 | s11 | s12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| s01 | 100 | | | | | | | | | | | |
| s02 | | 50 | | | | | | | | | 50 | |
| s03 | | | 100 | | | | | | | | | |
| s04 | | | | 33 | | 33 | 33 | | | | | |
| s05 | | | | | 100 | | | | | | | |
| s06 | | | | 33 | | 33 | 33 | | | | | |
| s07 | | | | 33 | | 33 | 33 | | | | | |
| s08 | | | | | | | | 50 | | | | 50 |
| s09 | | | | | | | | | 100 | | | |
| s10 | | | | | | | | | | 100 | | |
| s11 | | 50 | | | | | | | | | 50 | |
| s12 | | | | | | | | 50 | | | | 50 |
| $\overline{\lambda}_1$ | 2.58 | 3.04 | 2.75 | 2.32 | 2.41 | 2.34 | 2.31 | 2.67 | 2.87 | 2.09 | 3.03 | 2.69 |

## 7. COMBINING GAIT WITH FACE

Without preselection, the error in identification is quite high. With gait, the identification rate improves by as much as 92% as shown in Table 6. An example of correct identification is shown in Fig.10.

Table 6 Error rates of video FR / with gait fusion

| Person | No. of frames | Frames with faces | False id /fusion | | Error rate | Error/ fusion |
|---|---|---|---|---|---|---|
| | | | None | With | | |
| *s04* | 181 | 90 | 23 | 3 | 0.26 | 0.03 |
| *s06* | 125 | 23 | 21 | 4 | 0.91 | 0.17 |
| *s07* | 124 | 60 | 40 | 3 | 0.67 | 0.05 |

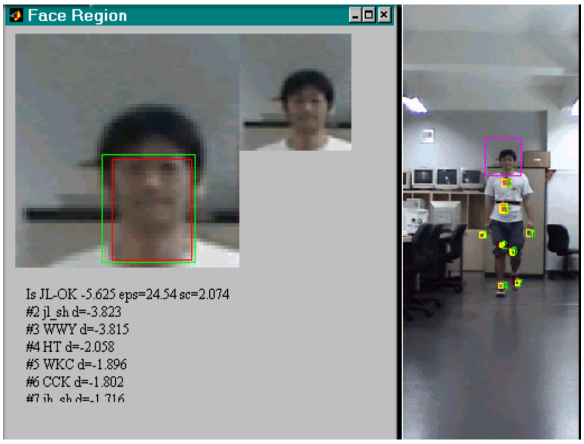


Fig. 10. Live face detect / recognition - correct id

## 8. 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 FN analysis of gait 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 $\lambda_1$ or with other biometrics are useful as well.

The use of $\overline{\lambda}_1$ with face recognition shows promise as a feature for classification. This paves the way for future work in this direction.

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