Quantifying and Recognizing Human Movement Patterns from Monocular Video Images - Part II: Applications to Biometrics

R. D. Green and L. Guan

Abstract – Biometric authentication of gait, anthropometric data, human activities and movement disorders are presented in this paper using the Continuous Human Movement Recognition (CHMR) framework introduced in Part I. A novel biometric authentication of anthropometric data is presented based on the realization that no one is average sized in as many as 10 dimensions. These body part dimensions are quantified using the CHMR body model. Gait signatures are then evaluated using motion vectors, temporally segmented by gait dynemes, and projected into a gait space for an *eigengait* based biometric authentication. Left-right asymmetry of gait is also evaluated using robust CHMR left-right labeling of gait strides. Accuracy of the gait signature is further enhanced by incorporating the knee-hip angle-angle relationship popular in biomechanics gait research, together with other gait parameters. These gait and anthropometric biometrics are fused to further improve accuracy. The next biometric identifies human activities which requires a robust segmentation of the many skills encompassed. For this reason, the CHMR *activity model* is used to identify various activities from making a coffee to using a computer. Finally, human movement disorders were evaluated by studying patients with dopa-responsive Parkinsonism and age matched normals who were video taped during several gait cycles to determine a robust metric for classifying movement disorders. The results suggest that the

---

R. D. Green is with the Human Interface Technology Lab, University of Canterbury, Christchurch, New Zealand. He was with the School of Electrical and Information Engineering, The University of Sydney, NSW 2006, Australia, (e-mail: richard.green@canterbury.ac.nz).
Prof. L. Guan is with the Department of Electrical and Computer Engineering, Ryerson University, Toronto, ON M5B 2K3, Canada (corresponding author: phone: +1-416-979-5000 ext. 6072; fax: +1-416-979-5280; e-mail: (e-mail: lguan@ee.ryerson.ca).

CHMR system enabled successful biometric authentication of anthropometric data, gait signatures, human activities and movement disorders.

1. Introduction

Although there is a large body of work describing computer vision systems for modeling and tracking human bodies (see [21] for a review), the vision research community has only recently begun to investigate gait as a biometric. Now, identifying humans from their gait is an extremely active area of computer vision [2, 4, 12, 15, 18, 19, 22, 23, 24, 30, 33]. This paper describes a robust gait metric with a novel left-step-right-step vector of spatial-temporal parameters to capture the left-right gait asymmetry of the population.

Collins recently combined body shape and gait into a single biometric applied to the gait databases from CMU (25 subjects), U.Maryland (55 subjects), U.Southampton (28 subjects) and MIT (25 subjects). Phillips reported a good 73% recognition rate on a larger sample of 74 subjects [28]. Instead of using a 2D shape based pose [6], this research employs a novel application of anthropometric dimensions from a 3D body used to uniquely identify individuals from the variability of physical proportions. Although previous work has been done on body-model acquisition from multiple cameras [20, 29], the clone-body-model was sized by the monocular CHMR system described in paper I.

Part II of this paper presents the biometric authentication of anthropometric data, gait signatures, human activities, and human movement disorders. These four biometrics depend on accurately quantifying and recognizing human body movement using a precise model of the body being tracked. This biometric authentication process is enabled with data from the CHMR system described in Part I of this paper which is used to non-invasively quantify and temporally segment continuous human motion in monocular video sequences. Relative dimensions from the CHMR *body model* support biometric identification from a library of anthropometric signatures. Gait signatures are correlated using dyneme segmented left-step-right-step motion vector arrays. General human movement activity identification is demonstrated using the CHMR *activity model* discussed in Part I of this paper.

Video image analysis is also able to provide quantitative data on postural and movement abnormalities and thus has an important application in neurological diagnosis and management. This paper describes an approach to classifying the gait of Parkinsonian patients and normal subjects using video image analysis results from the CHMR system.

2. Anthropometric Biometric

Vitruvius from 1st century B.C. Rome assumed all men were identically proportioned [34], as did Leonardo da Vinci with his famous drawing of the human figure, based on the Vitruvian norm-man (Figure 1). Later, more than 2000 years after Vitruvius wrote his ten books on architecture, Le Corbusier[7] revived interest in the Vitruvian norm with his mapping of human proportions (Figure 2) onto the *Golden Section* developed by Euclid in 300 B.C. Greece which Euclid had named the *extreme and mean ratio*.

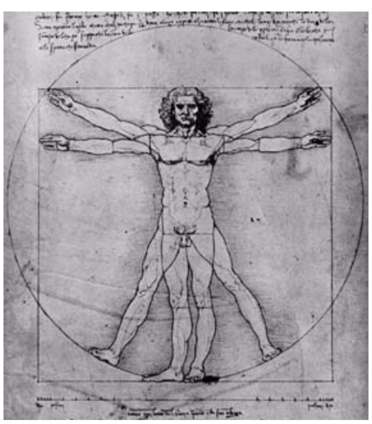


Figure 1. The *Vitruvian man* by Leonardo da Vinci.

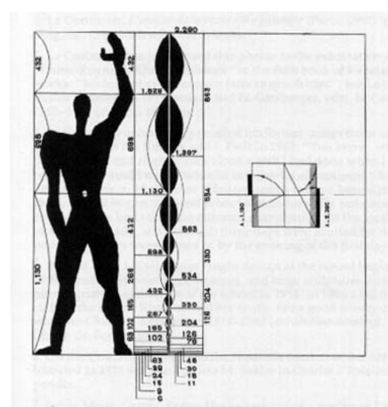


Figure 2. *Le Modulor* man by Le Corbusier.

However, this “average sized human” model assumed by Vitruvius, Leonardo da Vinci and Le Corbusier is a fallacy as there is no average sized person. A human with average proportions does not exist. More recent anthropometric data [27] shows that people who are average in two dimensions constitute only about 7% of the population; those in three, only about 3%; those in four, less than 2%. Since there is no-one who is average in 10 dimensions [13], a ten dimensional space of physical proportions can be used as a reasonably accurate biometric. What is not clear from anthropometric data is the natural asymmetry of the human body, which can also be utilized to further improve the accuracy of anthropometric authentication. This anthropometric asymmetry becomes apparent with one foot fitting a pair of shoes better that the other. This novel biometric promises maximal between-person variability while supporting minimal within-person variability across time within the adult population.

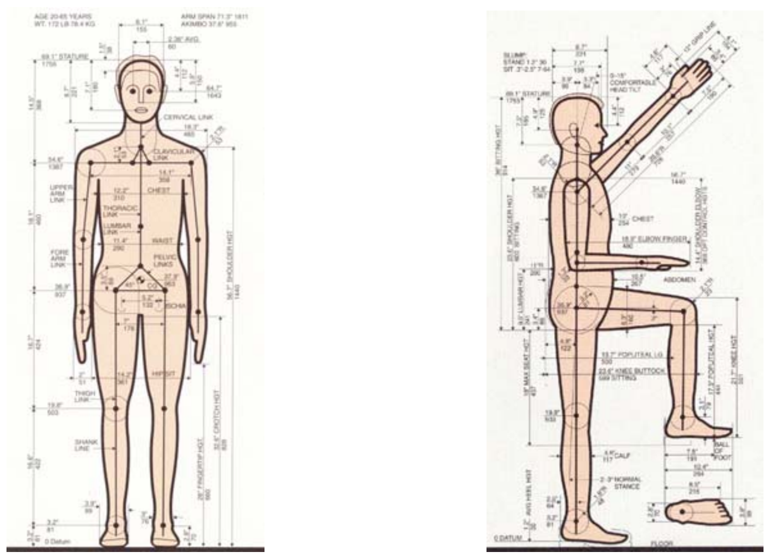


Figure 3. Front and side views of the 50th percentile proportions.
Drawings from H. Dreyfuss, *The Measure of Man*, 1978.

From initial 50th percentile anthropometric proportions (Figure 3), the body model used in the tracking process is automatically normalized and sized to the relative proportions of the person being tracked providing at least a ten dimensional space of physical proportions for this biometric measure. Anthropometric data [27] is also used to threshold variance from average body-part proportions allowing for age, race and gender. Each individual is represented by a normalized vector of physical proportions with associated accuracy weights from the CHMR clone-body-part averaged radius accuracy.

The tracking process maps each person into the training set with this anthropometric vector. The weights enable a confidence measure to be calculated and thresholded for a match.

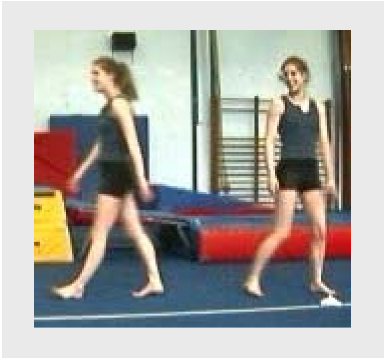


Figure 4. Turning and gait step overlaid, 58 frames apart.

Angular displacement of DOFs during gait enable ongoing improvement in body model accuracy as joint locations and body-part lengths become further revealed through the temporal resolution of self-occlusions. For example, turning 180^{o} to pace back significantly improves the accuracy of frontal dimensions as shown above in Figure 4.

3. Gait Signature

Approaches to gait recognition can traditionally be divided into two categories: *model based* and *holistic*. Holistic methods [28] derive statistical information directly from the gait image and attempt to correlate various features for biometric authentication. Initial results from holistic approaches are promising with recognition rates as high as 100% for small databases of hundreds of subjects. However, no research has been done to establish if these high recognition rates will translate to larger databases with thousands of subjects as in face-recognition or even millions of subjects as in iris-recognition [9]. Model based approaches rely on a model being fitted to the image data. Cunado [8] proposed a method for gait recognition based on moving feature analysis. The gait signature was extracted by using a Fourier series to describe the motion of the leg and temporally correlate this to determine the dynamic model from a sequence of images. Performance of this technique was also promising, with recognition rates of up to 90%, however the test sample was small.

Engaging a model based approach, the CHMR system is used to temporally segment *step* dynemes for which data from the motion vectors are analyzed to determine a unique gait signature. Similar to the static anthropometric left-right asymmetry of the body is the dynamic left-right asymmetry of gait. Accurate temporal segmentation and identification of the left and right steps is required to fully exploit this asymmetrical parametric diversity of gait populations. In a new approach to biometric authentication of gait, this asymmetry is quantified using the motion vectors given the differentiated left and right step segmentation from the CHMR system.

A gait pattern classifier takes a temporally normalized sequence of gait delimited motion vectors as the input feature vector – essentially two alternate *step* dynemes. An *eigengait* approach [3] is employed in which a similarity plot is treated the same way that a face is recognized in the *eigenface* approach by Pentland et al. [26] with a similar novel *eigenspike* approach applied successfully by one of the authors to identify epileptic spikes [10,17]. The motion vectors of left-right step dyneme pairs are found to be the principal components of the distribution of the feature space. This is followed by standard pattern classification of new feature vectors in the lower-dimensional space spanned by the principal components.

Normalized left and right stride-dyneme motion vectors are concatenated into one single vector. The right stride is appended to the left stride to form a single gait vector $\boldsymbol{g}$ for each person. For recognition, a gait vector is projected into a reduced set of basis vectors. These basis vectors are the global eigenvectors associated with the largest eigenvalues of a covariance matrix of the training set of N people ($g_1..g_N$) found by the eigenvalue decomposition of their covariance matrix:

$$C_g = \frac{1}{N}\sum_{i=1}^{N}(g_i - \overline{g})(g_i - \overline{g})^{\mathrm{T}} \quad (1)$$

where $\overline{g}$ is the mean of the training set. Each gait vector g_i is approximated by an n-dimensional vector w_i obtained by projecting it into the space spanned by the n most significant eigenvectors, $u_1..u_n$:

$$w_i = \sum_{j=1}^{n} u_j^{\mathrm{T}} g_i \tag{2}$$

Of particular interest is the knee-hip angle-angle relationship popular in biomechanics gait research especially since the minimum possible gait DOFs would include only the hip and knee flexions. In this research, left-right gait asymmetry as a gait feature is explored by using the robust CHMR left-right labeling of gait strides to enable a robust phase alignment of the alternating steps, further enhancing the accuracy of this metric.

Gait and anthropometry have the advantage over other biometrics such as fingerprint and iris in that they are non-invasive to the extent that the subject may not know they are being recognized in security and surveillance applications. The gait and anthropometric biometrics also have the proximity advantage over face detection since they can operate on a lower resolution image. With the CHMR approach, it is possible to fuse the gait and anthropometric biometrics to improve the accuracy.

4. Activity Identification

Research into human activities generally represents an activity as a single skill such as *walk, run, turn, sit,* and *stand* [31]. This is problematic since human activities are often more complex consisting of a sequence of many possible skills. An activity can be more accurately defined as a sequence of one or more core skills. This research seeks to broaden the distinction between activity and skill. The CHMR activity model in Part I defines possible human movement activities that the search can hypothesize, representing each activity as a sequence of one or more core skills.

For example, making a coffee consists of the minimum sequence "spoon-coffee, pour-water". Many other potential skills exist in the make-coffee sequence with *pre-skills* such as "boil-water, get-cup, get-spoon" and *post-skills* such as "stir-coffee, carry-cup". Therefore a set of zero or more related pre and post skills are associated with each activity to enable the temporal grouping of skills relating to a particular activity. In this way, not only are a sequence of motion vectors temporally segmented into a skill, but a sequence of skills can be temporally segmented into an activity.

Five activities were performed, each by three people:

1. coffee: making a coffee
2. computer: entering an office and using a computer
3. tidy: picking an object off the floor and placing it on a desk
4. snoop: entering an office, looking in a specific direction and exiting
5. break: standing up, walking around, sitting down

Although an attempt was made to track lifting a coffee pot, carried objects are not recognized as separate from the human body and so tend to destabilize the human body, depending on their size. This research does not cover models beyond a human body model. Consequently, holding large objects such as a coffee pot destabilizes the tracking due to the body part holding the object being dimensioned beyond an acceptable anthropometric threshold. Hence, the activities were defined in this paper did not involve carrying objects larger than a small coffee cup.

The CHMR system is utilized to recognize various activities from making a coffee to using a computer. The CHMR activity model defines the possible human movement activities that the search can hypothesize, representing each activity as a linear sequence of skills. This activity biometric is discussed and tested further in this paper.

5. Movement Disorders

Patients with neurological disorders frequently show some degree of gait abnormality. A typical example is Parkinson’s disease (PD). Common motor symptoms of PD include: rhythmic shaking of one or occasionally more limbs (tremor), slowness in movement (bradykinesia), stiffness of joints (rigidity), slightly bent and flexed posture, and failure of the arms to swing freely when walking [25].

Walking is a highly refined, remarkable and automatic skill of humans which is easily taken for granted. The basic reflex for walking, which is probably located in the spinal cord, is present at birth. Parents, relatives and friends are all very pleased, excited and proud when an infant takes the first steps. At the other end of the time spectrum, abnormalities of gait and falling tend to be problems of the elderly. Disorders of gait and mobility are second only to impaired mental function as the most frequent neurological effects of aging. Normal gait, stance and balance require precise input from proprioceptive (position sense), vestibular (inner ear mechanisms and their connections within the brain stem) and visual pathways as well as auditory and tactile information. Two of the three major afferent systems (proprioceptive, vestibular and visual) must be intact to maintain balance. Afferent data must be integrated in the brain stem and brain through motor (pyramidal and extrapyramidal) and cerebellar pathways, which then serve as the efferent arc of the important skill of walking. Dysfunction in the afferent or efferent systems or in the central integrating centers can lead to gait problems. Gait disorders in the elderly are frequently heterogeneous and often multi-factorial in origin.

The function of the extrapyramidal system is to modulate posture, right reactions and associated movements. The Parkinsonian gait is characterized by a flexed posture, diminishing arm swing and rigid, small-stepped, shuffling gait. Arising from a sitting position may be slow or impossible. Patients often have difficulty with initiation of movement and turns. Disturbances of balance are often present (impairment of postural reflexes). The legs are stiff and bent at the knee and hips. As the patient walks, the upper part of the body gets ahead of the lower part and the steps become smaller and more rapid (festination). Turning is accomplished with multiple unsteady steps, with the body turning as a single unit (en bloc).

The clinical approach to gait analysis is heavily dependent on subjective observation of the patient’s gait. Although the reliability of subjective observation may be improved by systematic procedures and rating scales, the asynchronous series of changes in the complex articulated assembly of the human body presents such a maze of data that few persons could assimilate them all. This limitation may be minimized by quantitative documentation of the patient’s performance with reliable instrumentation to provide a permanent record of fact. Quantitative gait analysis is an important clinical tool for quantifying normal and pathological patterns of locomotion and has been shown to be useful for prescription of treatment as well as in the evaluation of the results of such treatment [1].

Commercial quantitative video analysis techniques require patients to be video taped while wearing joint markers in a highly structured laboratory environment with extensive set-up procedures. This limits the usefulness of video based analysis in routine clinical practice and so it is rarely used in this capacity. Current video analysis would also be unable to analyze existing video tape libraries[1]. Based on the CHMR model discussed in Part I, this paper presents a video analysis system, free of markers and set-up procedures, which quantitatively identifies gait abnormalities in real-time. The aim in this research is to develop a system able to meet the needs of a busy movement disorders clinic in both on-line and off-line analysis and diagnosis.

6. Performance

Gait sequences and activity skills were tracked and classified using a 1.8GHz, 640MB RAM Pentium IV platform processing 24 bit color within the Microsoft DirectX 8.1 environment under Windows XP. The video sequences were captured with a JVC DVL-9800 digital video camera at 30 fps, 720 by 480 pixel resolution.

Each person moved in front of a static blue-screen background with constant lighting conditions and no foreground object occlusion. Only one person was in frame at any one time. Tracking began when the whole body was visible which enabled initialization of the body model. Each person walked parallel to the image plane in front of a stationary camera, and then turned to walk back again, repeating this sequence five times on average. The body model accuracy was significantly improved by the first turn. The first turn also enabled accurate texture mapping of the occluded side and the varying perspectives of the body enabled radii to be more accurately determined as shown in Figure 5. The large number of frames available in a single turn is of considerable benefit to accurately dimensioning the body model.

---

[1] Such as the Westmead Hospital Movements Disorders Clinic in Sydney which has accumulated a large patient library.

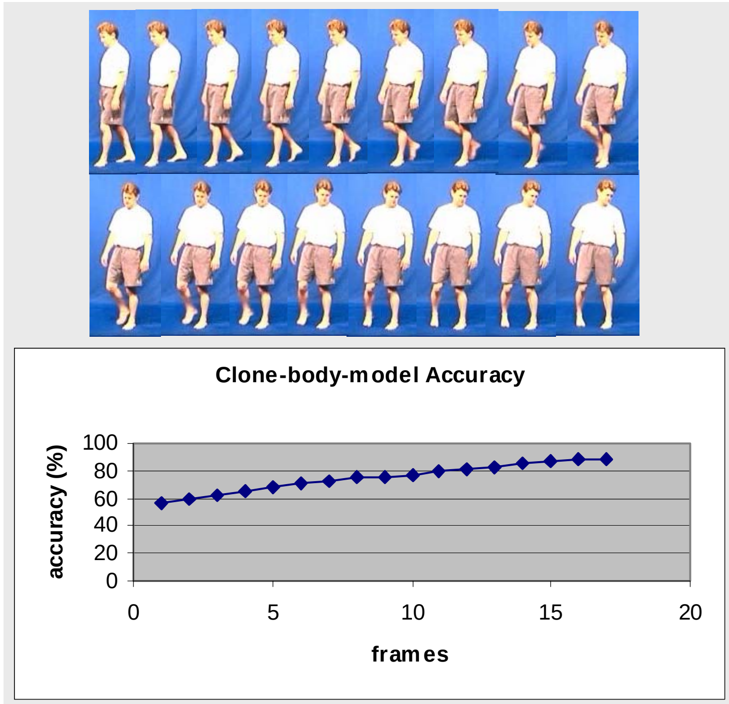


Figure 5 Tracking the combined average clone-body-part radius ($\sum a_r/\sum b$) and color accuracy ($\sum a_{hsi}/\sum b$) over 17 frames during a turn phase illustrates more dimensions being revealed to further increase clone-body-model accuracy.

For completeness, biometric results are less ambiguously quantified using five categories: correctly recognized (true positive), incorrectly recognized, correctly rejected (true negative), false negatives and false positives. False negatives represent incorrectly rejected candidates from the training set and false positives are incorrectly recognized candidates not present in the training set. The performance of the anthropometric and gait biometrics is presented in the following sections using these five categories of results.

6.1 Anthropometric Biometric

Training samples of 48 people in tight clothing are represented by vectors of physical proportions with associated accuracy weights. The tracking process also attempted to recognize 10 people who were not present in the training gallery. The weights enable a confidence measure to be calculated and thresholded for a match.

Based on the training data, a recognition rate of 92% was achieved for the anthropometric biometric for a confidence threshold of 99% with one false positive. Dimension inaccuracies were reduced by tight fitting clothes being worn by the training and test samples. Accuracy of body proportions was significantly improved by the first turn due to varying perspectives of the body which enabled radii to be more accurately determined.

Correct recognition	Incorrect recognition	False negative		Correct rejection	False positive
92%	2%	6%		90%	10%

Table 1. Biometric authentication of anthropometric data.

In Table 1, false negatives represent incorrectly rejected candidates from the training set and false positives are incorrectly recognized candidates not present in the training set. It was found that dimension inaccuracies are introduced by hair, footwear and thick clothes such as heavy woolen sweaters. Consequently, some head dimensions were weighted low due to hairstyle induced inaccuracies. Similarly, foot dimension weights were also low due to adverse footwear influence. It was found that large loose clothes such as coats, skirts and dresses occluded body parts causing the body model to fail to initialize for tracking due to the variance of body-part proportions exceeding an acceptable threshold.

6.2 Gait Signature

A sample of 48 people walking in a sagittal plane became the training gallery, with an additional 10 unknowns. Reasonably tight fitting clothes were worn by all 58 people with no severe self-occlusions of both legs, which would cause this approach to fail. The two most significant gait biometric predictors were found to be the knee-hip angle-angle relationship and the left-right asymmetry of that relationship, being a subset of the left-right step-dyneme vector. Figure 6 illustrates the uniqueness of these angle-angle relationships by overlaying the knee-hip diagrams of four different people.

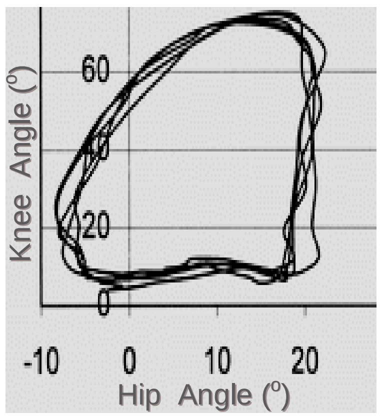


Figure 6. Hip-knee angle-angle relationships of four different people.

Gait specific features were normalized with respect to the gait cycle. The principal components were found for the distribution of the feature space of gait-step dyneme pairs by standard pattern classification of new feature vectors in the lower-dimensional space spanned by the principal components. This *eigengait* analysis yielded the same recognition rate of 88% as the hip-knee angle and asymmetry fusion.

Gait feature %	Correct recognition	Incorrect recognition	False negative	Correct rejection	False positive
Gait period	48	32	20	60	40
Arm swing amplitude	64	14	22	70	30
Stride amplitude	66	22	12	60	40
Arm swing asymmetry	76	6	18	80	20
Hip-knee angle-angle	82	6	12	90	10
Hip-knee left-right asym.	86	4	10	90	10
Hip-knee angles & asym.	88	2	10	100	0
Eigengait analysis	88	0	12	100	0

Table 2. Gait signature recognition results.

In Table 2, false negatives represent incorrectly rejected candidates from the training set and false positives are incorrectly recognized candidates not present in the training set. Interestingly, the fusion of both the anthropometric biometric and gait biometric raised the accuracy from 92% and 88% respectively, to 94%.

About 30% of subjects moved their arms minimally causing the far arm to be occluded during the gait cycle, to be accurately measured only when walking back in the opposite direction. It was assumed that the near side visible arm swung identically when it was occluded. The large number of small arm swing amplitudes accounts for the low 64% gait signature recognition based on arm amplitude and 76% recognition based on arm swing asymmetry. In future studies involving carried objects [6], arm swing will become less relevant to the gait signature.

6.3 Activity Identification

The activity error rate quantifies CHMR system performance by expressing, as a percentage, the ratio of the number of activity errors to the number of activities in the reference training set. The CHMR system was tested on a training set of five activities with an activity error rate of 0%. However the sample size is too small for this result to be significant.

Activity %	Recognition	False negative
Coffee	100	0
Computer	100	0
Tidy	100	0
Snoop	100	0
Break	100	0

Table 3. Activity recognition results.

Results for the following activities are detailed in Table 3 above.

- coffee: making a coffee
- computer: entering an office and using a computer
- tidy: picking an object (pen) off the floor and placing it on a desk
- snoop: entering an office, looking in a specific direction and exiting
- break: standing up, walking around, sitting down

With such a small sample of activities, the activity recognition results reflect the skill recognition results of 4.5% skill error rate in Part I.

Although carrying a spoon in *coffee* and a pen in *tidy* caused no tracking problems, attempts to carry objects such as a large mug caused the arm to permutate through unexpected angles within an envelope sufficiently large as to invalidate the tracking and recognition. Carrying even larger objects such as a brief-case caused the body model to fail. With no valid body to track, tracking and recognition did not proceed. It is intended to extend the tracking process to recognized carried objects as separate from the human body for a more useful activity recognition biometric.

6.4 Movement Disorders

The gaits of twenty patients with dopa-responsive Parkinsonism (PD) and fifteen aged matched normals were tracked and classified. The PD video data analyzed in this paper was validated in a previous study [14,32,5].

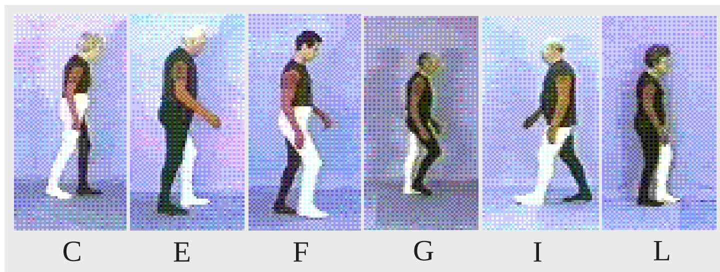


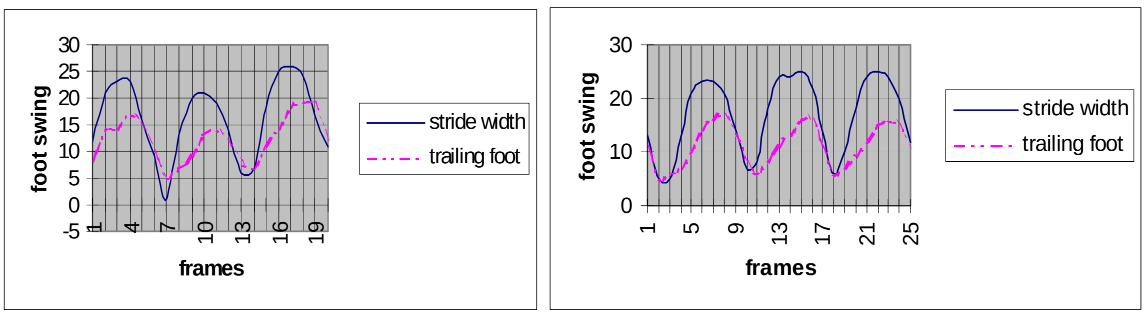
Figure 6. PD gait samples illustrating characteristic body flexion with asymmetrical or minimal arm swing.

A number of gait parameters were analysed to determine their significance to the correlation of PD gait. These features included: leg swing, arm swing, gait period and shape of the gait cycle limb swing waveform. The PD limb swing amplitude was generally less than that of normals, but it was found to vary among both PDs and age matched normals enough to result in about 11% false positives and so was not a useful feature (refer to Table 4). The period of the gait was also unable to reliably classify PD gait. The most useful feature proved to be the left-right asymmetry of waveform shape due to a significant asymmetry in the PD gait arising from the deterioration of one side more quickly than the other. Using this feature, the system correctly classified 95% of subjects with one false negative.

%	Correct PD	False negative		Correct normal	False positive
Amplitude: leg	90	10		80	20
arm	85	15		73	27
Gait period	55	45		88	12
Gait asymmetry	95	5		93	7

Table 4: Correlation of limb swing amplitude, period and left-right asymmetry.

The two graphs in Figure 7 illustrate this PD asymmetry by contrasting an irregular PD gait with the regular leg swing of a normal gait. PD patients in Figure 6 show either no arm swing (subjects C, G and L) or the significant asymmetry typical of PD gait (subjects E, F and I). Also visible was the flexed body and limb shape (subjects C, E, F and G) common in PD. This contrasts with the somatotype and age matched normals in Figure 8. The degree to which body and limbs were flexed was not addressed by this study.



PD gait

Normal gait

Figure 7. Graphs contrasting an asymmetrical leg swing typical of PD gait with a normal symmetrical gait.

The single PD gait sample not detected by this system had a gait similar to normal but some tremor was visible. However, due to the low resolution images and low frame rate, tremor was not able to be analysed. Another problem arose from the minimal arm swing common in PD gaits. With minimal arm swing in many PD gaits, tracking the far arm caused problems because it was occluded during entire gait passes. To stabilise tracking in this case, the location of the far arm was assumed to be near vertical or similar to the location of the near arm.

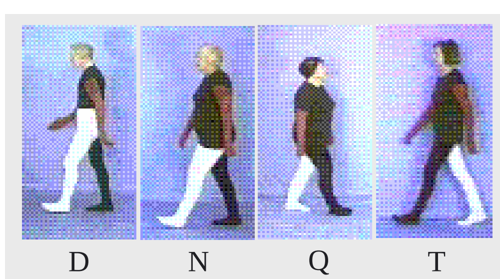


Figure 8. Aged matched normal gait samples.

The subjects used in this study had been used in a previous study and were therefore established as known PDs and normals. The classification accuracy was improved in this study by analysing entire gait cycles rather than a static gait snapshot of each subject as in the previous study.

7. Conclusions and future research

This research has demonstrated that the proposed CHMR system, presented in Part I, tracked and recognized not only hundreds of skills, but also successfully applied biometric authentication to anthropometric data, gait signatures, human activities and movement disorders. In this paper these biometrics were recognized free of joint markers, set-up procedures and hand-initialization. CHMR body model data was successfully applied as a biometric for body proportions and gait dyneme segmented motion vectors successfully supported a biometric for gait signatures.

A novel biometric authenticating anthropometric data was presented in this paper based on a maximal between-person variability of about ten dimensions of body proportions with promising minimal within-person variability across time. A recognition rate of 92% was achieved with one false positive supporting this anthropometric signature as a valid biometric

Biometric authentication of gait signatures achieved 88% recognition with no false positives using the eigengait approach Although this is better than the 73% reported by Phillips [28], it is not as good as others have achieved for smaller sample sizes [3]. The most significant gait feature was found to be the left and right hip-knee angle-angle relationship encompassing a left-right asymmetry. Fusion of anthropometric and gait biometrics raised the accuracy from 92% and 88% respectively, to 94%. These results indicate that applying a fused anthropometric-gait biometric authentication could form the basis for a security application. Future studies will extend to fast and slow gaits of each subject and include carried items.

Human movement activities were identified with no activity error. Various activities from using a computer to making a coffee were successfully tracked and recognised. However the number of activities in the sample were too small for this result to be conclusive.

In this paper, it was also demonstrated that this approach was able to successfully track and classify gait to detect PD with a success rate of 95% with one false positive. The results suggest that this approach has the potential to guide clinicians on the relative sensitivity of specific postural/gait features in diagnosis and quantifying progress. However, detecting the small rapid motion of tremor would necessitate a higher frame rate and resolution than was used in this study.

Future studies aim to extend the skill, semantic and activity models and also to improve the robustness and accuracy of the system, especially the poorly observable depth DOFs, by applying to the Particle filter, inflated posteriors and dynamics for sample generation and then reweighing the results. Future research will adopt Receiver Operating Characteristic (ROC) methodology using ROC curves to present results for more clarity.

Loose clothing and carried items which occluded body parts reduced the effectiveness of these biometrics. An improvement can be achieved by modeling the draping of loose clothing to more fully reveal the true body shape [16]. The body model also needs to be extended to allow for the wide variety of loose clothing encountered in general situations. Tracking stability can also be increased by enhancing the body model to include degrees of freedom supporting radioulnar (forearm rotation), interphalangeal (toe), metacarpophalangeal (finger), and carpometacarpal (thumb) joints to further stabilize the hand and feet positions.

Future studies also aim to further improve the accuracy of the biometric authentications presented in this paper by increasing sample sizes and both the spatial and temporal resolutions.

6. References

[1] T P Andriacchi, J O Galante, R W Fermier, The influence of total knee-replacement design on walking and stair climbing, *J Bone Surg*, American, 64: 1328-1335, 1982.

[2] C BenAbdelkader, A Cutler, H Nanda, L Davis. Eigengait: Motion-based recognition of people using image selfsimilarity. *3rd International Conference on Audio- and Video-Based Biometric Person Authentication*, June 2001.

[3] C BenAbdelkader, R Cutler, L Davis, Person Identification Using Automatic Height and Stride Estimation, *IEEE Int. Conf. on Pattern Recognition*, Québec City, Canada, August 2002.

[4] A F Bobick, A Y Johnson, Gait recognition using static, activity-specific parameters, *IEEE Computer Vision and Pattern Recognition*, I: 423–430, 2001.

[5] R Chang, L Guan, J A Burne, An Automated Form of Video Image Analysis Applied to Classification of Movement Disorders, *Journal of Disability and Rehabilitation*, 22(1/2): 97-108, January/February 2000.

[6] R T Collins, R Gross and J Shi, Silhouette-based Human Identification from Body Shape and Gait, *IEEE Int. Conf. on Automatic Face and Gesture Recognition*, May, 2002

[7] Le Corbusier, *The Modulor*, Harvard University Press, Cambridge, MA, 1955.

[8] D Cunado, M Nixon, J Carter, Gait Extraction and Description by Evidence Gathering, *2nd Int. Conf. on Audio and Video-Based Biometric Person Authentication*, 1999.

[9] J Daugman, How Iris Recognition Works, *IEEE Conf. on ICIP*, 2002.

[10] R Green, Detection of epileptiform discharges in the electroencephalogram: Real-time processing and Eigenspikes in neural networks, Unpublished ME Thesis, Electrical & Electronic Engineering, University of Canterbury, Christchurch, 1995.

[11] R Green, L Guan, J A Burne, Real-time gait analysis for diagnosing movement disorders, *Journal of Electronic Imaging*, 9(1): 16-21, January, 2000.

[12] J Hayfron-Acquah, M Nixon, J Carter. Automatic gait recognition by symmetry analysis. *3rd International Conference on Audio and Video-Based Biometric Person Authentication*, June 2001.

[13] H T E Hertzberg, *Engineering anthropology. Human engineering guide to equipment design (2nd ed.)*. Government Printing Office, Washington, DC, US, 1972.

[14] P S Huang, C J Harris, M S Nixon, Comparing Different Template Features for Recognizing People by their Gait, *BMVC*, 1998.

[15] A Johnsson, A Bobick. A multi-view method for gait recognition using static body parameters. *3rd International Conference on Audio- and Video-Based Biometric Person Authentication*, June 2001.

[16] N Jojic, J Gu, H C Shen, T S Huang, Computer Modeling, Analysis, and Synthesis of Dressed Humans, *IEEE Transactions on Circuits and Systems for Video Technology*, 9(2): 378-388, 1999.

[17] R D Jones, A A Dingle, G J Carroll, R D Green, M A Black, I M Donaldson, et al. *A system for detecting epileptiform discharges in the EEG: Real-time operation and clinical trial*, Proc. of 18th Int. Conf. of the IEEE Engineering in Medicine and Biology Society, Amsterdam, The Netherlands, Vol. 18, pp. 948-949, 1996.

[18] J J Little, J E Boyd. Recognizing people by their gait: The shape of motion. *Videre (online journal)*, 1(2), Winter 1998.

[19] D Meyer, J Posl, H Niemann. Gait classification with HMMS for trajectories of body parts extracted by mixture densities. *BMVC98*, 1998.

[20] I Mikic, M Triverdi, E Hunter, P Cosman. Articulated body posture estimation from multi-camera voxel data. *Computer Vision and Pattern Recognition*, 2001.

[21] T B Moeslund, E Granum, A survey of computer vision-based human motion capture, *Computer Vision and Image Understanding*, 18: 231–268, 2001.

[22] H Murase, R Sakai. Moving object recognition in eigenspace representation: Gait analysis and lip reading. *Pattern Recognition Letters*, 17(2): 155–162, February 1996.

[23] M Nixon, J Carter, D Cunado, P Huang, S Stevenage. Automatic gait recognition. *Biometrics: Personal Identification in Networked Society*, 231–249. A Jain, R Bolle, S Pankanti, editors, Kluwer Academic Publishers, 1999.

[24] S A Niyogi, E H Adelson. Analyzing and recognizing walking figures in xyt. *IEEE Proceedings Computer Vision and Pattern Recognition*, 469–474, 1994.

[25] J Pearce, *Parkinson's disease and its management*, Oxford University Press, New York, USA, 1992.

[26] A Pentland, B Moghaddam, T Starner *View-Based and Modular Eigenspaces for Face Recognition*, Proc. of IEEE Conf. on Computer Vision and Pattern Recognition, 1994.

[27] S Pheasant, *Bodyspace. Anthropometry, Ergonomics and the Design of Work*, Taylor & Francis, 1996.

[28] P J Phillips, S Sarkar, I Robledo, P Grother, K Bowyer. Baseline Results for the Challenge Problem of Human ID Using Gait Analysis. *5th IEEE International Conference on Automatic Face and Gesture Recognition*, May 2002.

[29] R Plänkers, P Fua, N D'Apuzzo, Automated body modeling from video sequences. *IEEE International Workshop on Modelling People (mPeople)*, Corfu, Greece, September, 1999.

[30] G Shakhnarovich, L Lee, T Darrell. Integrated face and gait recognition from multiple views. *IEEE Computer Vision and Pattern Recognition*, I: 439–446, 2001.

[31] X Sun, C Chen, B Manjunath, *Probabilistic Motion Parameter Models for Human Activity Recognition*, IEEE Int. Conf. on Pattern Recognition Québec City, Canada, August 2002.

[32] T Tan, L Guan, J A Burne, *A Real-Time Image Analysis System for Computer-Assisted Diagnosis of Neurological Disorders*, J. of Real-time Imaging, Vol. 5, No. 4, pp. 253-269, August, 1999.

[33] R Tanawongsuwan, A F Bobick. Gait recognition from time-normalized joint-angle trajectories in the walking plane. *IEEE Computer Vision and Pattern Recognition*, II: 726–731, 2001.

[34] Vitruvius, *De Architectura*, Book 3, c. I(1), 1st century BC.