2001

Application of Digital Image Processing to Marker-free Analysis of Human Gait

Jane Courtney
Technological University Dublin, jane.courtney@tudublin.ie

David Burke
University College Dublin

Annraoi dePaor
University College Dublin

Recommended Citation

Courtney, J, Burke, David, J., dePaor, A. (2001) Application of Digital Image Processing to Marker-free Analysis of Human Gait, *MEASUREMENT SCIENCE REVIEW,* Vol. 1, no.1.

2001

Application of Digital Image Processing to Marker-free Analysis of Human Gait

Jane Courtney

David P. Burke

Annraoi dePaor

Application of Digital Image Processing to Marker-free Analysis of Human Gait

By Jane Courtney, David P. Burke, Annraoi M. de Paor

National University of Ireland, Dublin, Belfield, Dublin 4 and Engineering Research Laboratory, National Rehabilitation Hospital, Dún Laoghaire, Co. Dublin. E-mail: david.burke@ucd.ie

Abstract
The standard method of human gait analysis in use in gait laboratories today invariably involves marker-based motion tracking systems. Although somewhat effective, these methods require accurate placement of awkward external markers. We report on an enhanced approach being researched and developed at the National Rehabilitation Hospital, Dublin based on marker-free motion tracking incorporating advanced digital image processing techniques.

Introduction
Many therapists and doctors rely on gait analysis to monitor efficacy in patient treatment, allowing the results of various types of gait therapy to be quantified and therefore more accurately compared and contrasted. The first recorded attempts to understand the process of animal movement date back to Aristotle circa 350 BC [1]. Aristotle formulated theories on the control of movement and even suggested a theoretical experiment to measure human gait: "…if a man were to walk alongside a wall (with a reed dipped in ink attached to his head) the line traced would not be straight but zigzag because it goes lower when he bends and higher when he stands upright…" Although science has advanced considerably since Aristotle's time, in particular by the now ubiquitous video recording methods, a new problem has arisen: To get an accurate trace of the patient's locomotion it is necessary to use some kind of markers on the joint centres. This is often achieved by externally attached markers, which reflect ultra-violet light into purposed built cameras. This method, however suffers from a number of issues. Accurate placement of markers, which must stay in position throughout data recording, is critical to the accuracy of the derived clinical indices. Also, markers can restrict the normal gait of a patient as can the feeling of self-consciousness while walking in under garments.

Marker free gait analysis tries to alleviate some of these problems. It is still a relatively new concept and although there are a few basic commercially available systems e.g. [3], marker-free gait analysis is still very much in the development stages. We present a report on our findings from analysis and development of such a system in conjunction with the medical staff at the National Rehabilitation Hospital. We present the methods used, followed by results of the application. We conclude with a discussion on future goals.

Image Processing Methods
We have developed a system based on real-time analysis of acquired video data. This data manifests itself as a stream of matrices of triplets where each matrix location corresponds directly with a pixel location in the image and each triplet describes the relative intensity of the primary colours red, green, and blue. We have restricted ourselves to the problem in the sagittal plane and concentrated on describing the motion of the calf and thigh thus affording us accurate tracking of the knee. Briefly,

our approach involves a four step pre-processing method followed by a model fitting exercise. The initial steps employ a combination of *background subtraction*, *thresholding*, *edge detection*, and application of the *Chamfer distance transform*. We outline the concepts involved in each step and conclude with a description of our model-fitting algorithm.

Background Subtraction

Conceptually this is probably the simplest operation we perform: the background image is sampled and subtracted from each successive frame. This is similar to the classic blue-screening[1] method used in television production, although in our case we assume a very dark background colour.

Thresholding

Given the intensity of a pixel i,j written as $I(i,j)$ we define the threshold matrix T as

$$\begin{aligned} T(i, j) &= 1 \text{ for } I(i, j) \geq thresh \\ T(i, j) &= 0 \text{ for } I(i, j) < thresh \end{aligned} \tag{1}$$

By multiplying each element in matrix T by its corresponding element in I, we obtain an image where pixels of intensity less than a given threshold are removed. This operation is performed after background subtraction to take into account the possible loss in intensities of the foreground by a non-ideal black background.

Edge Detection

Edge detection is performed by examining the gradient between adjacent pixels. A first approximation is obtained by

$$E(i, j) = I(i, j) - I(i, j-1) \tag{2}$$

This operation can be conveniently performed by application of a *mask*, i.e. given

$$\begin{pmatrix} a & b & c \\ d & e & f \\ g & h & i \end{pmatrix} \tag{3}$$

we can obtain its *discrete convolution* with an image of intensities I according to

$$\begin{aligned} R(i, j) = {} & a.I(i-1, j-1) + b.I(i-1, j) + c.I(i-1, j+1) + d.I(i, j-1) + \\ & e.I(i, j) + f.I(i, j+1) + g.I(i+1, j-1) + h.I(i+1, j) + i.I(i+1, j+1) \end{aligned} \tag{4}$$

An optimisation on the first difference operation to detect edges that caters for discontinuous edges and inhomogenetics in a region while accentuating verticals and diagonals uses the so-called the *Sobel (diagonal) masks* [4]:

$$\begin{pmatrix} -2 & -1 & 0 \\ -1 & 0 & 1 \\ 0 & 1 & 2 \end{pmatrix} \qquad \begin{pmatrix} 0 & -1 & -2 \\ 1 & 0 & -1 \\ 2 & 1 & 0 \end{pmatrix} \tag{5}$$

Figure 1 illustrates the effect sequentially applying our first three data processing algorithms (and thresholding the edge detected image):

[1] Actually the colour of the screens are green

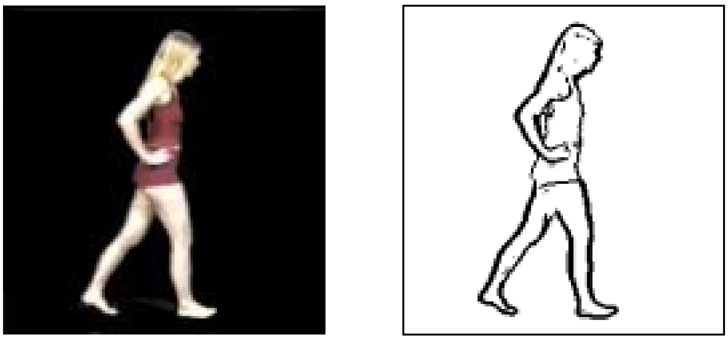

Figure 1

Chamfer Distance Transform

To aid in model fitting we apply the Chamfer Distance Transform [2], which converts the edge-detected image to a distance map. A distance map is essentially a grey level image where the pixel intensity is determined by its distance from the nearest edge. Given the general equation for a mask we form the distance map matrix R from

$$R(i, j) = \min(I(i-1, j-1) + a, I(i-1, j) + b, I(i-1, j+1) + c, I(i, j-1) + d, I(i, j) \\ + e, I(i, j+1) + f, I(i+1, j-1) + g, I(i+1, j) + h, I(i+1, j+1) + i) \qquad (6)$$

Using the Eulcidean distance [2] yields the following normalised mask

$$\begin{pmatrix} \sqrt{2} & 1 & \sqrt{2} \\ 1 & 0 & 1 \\ \sqrt{2} & 1 & \sqrt{2} \end{pmatrix} \qquad (7)$$

Model Fitting

The final stage of our method sees a wire-frame model consisting of 4 lines fit the femur and tibia portions of a leg. The user must first initialise the hip, knee, and ankle joints by simply clicking on them. The line is then expanded laterally until an edge is located. The six line endings are joined as illustrated in the distance transformed image of figure 2.

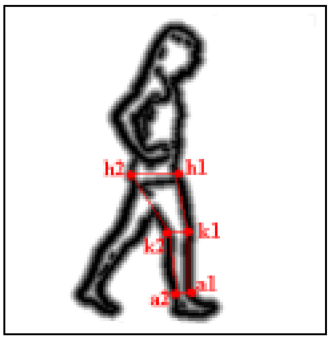

Figure 2

The model must now be dynamically updated across frames. This is achieved by rotating each of the four lines separately around each of its ends and finding the best fit defined by the minimum value for the *pixel-sum*. The pixel-sum is obtained from a summation of the pixel intensities corresponding to each pixel of a line in the distance transformed image. Finally, the joint positions can be calculated by determining the intersection of the midlines and the lateral lines.

Results

All software was developed for an Intel based platform running Windows. The C++ programming language was chosen for its superior speed of its compiled code. As an initial step we have remove one of the legs of the image, which can cause errors in the modelling algorithm. Figure 3 illustrates an example of some data acquired and modelled.

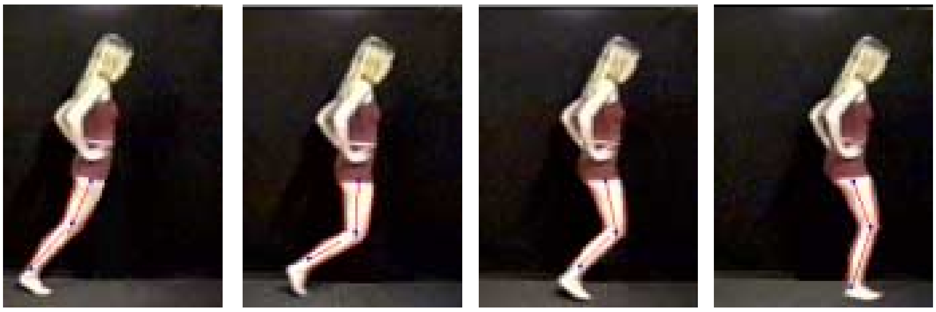

Figure 3

Based on the model, we have extracted the vertical knee position (which is a powerful clinical index) as illustrated in figure 4.

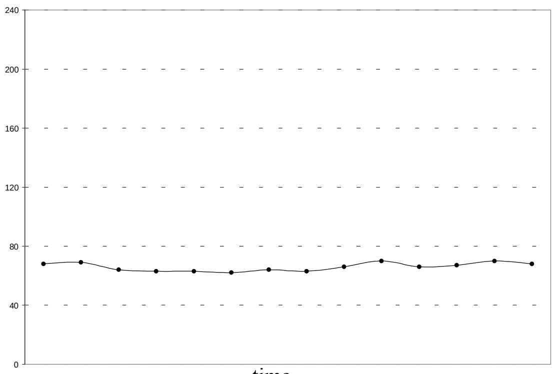

Figure 4

Discussion

Initial results have proven quite promising. Further indices can be obtained by including information relating to the foot and shoulder. We are currently developing predictive algorithms to allow tracking of both legs. In addition, we are actively researching the possibility of generating a 3D model (using two cameras) based on rhombus models of the limbs.

References

[1] Aristotle, *Parts of Animals* in Movement of animals, progression of animals, Peck A L (translator), Harvard University Press, Cambridge MA, 1937

[2] Toriwaki, J I, Kato, N and Fukumura T, "Parallel local operations for a new distance transformation of a line pattern and their applications" *IEEE Trans. System, Man, Cyb*, vol SMC-9, no. 10, 628-643, 1979

[3] http://www.mikromak.com

[4] Parker, J R, *Practical Computer Vision Using C*, Wiley, Somerset, 1994