ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 4, Special Issue 19, April 2017

Video Based Rehabilitation Analysis in Gait Training System

B.PRIYA, F.SHAKINA BEGUM, A.K.RAMANATHAN (AP/ECE)
Department of Electronics and Communication Engineering.
Dhaanish Ahmed College of Engineering.

Abstract- This paper presents a new portable motion capture and gait analysis system for capturing and analyzing human gait, designed as a telemedicine tool to monitor remotely the progress of patients through treatment. The gait video can be filmed in any reasonable environment without significant restriction. The design uses a Histogram of oriented gradient (HOG) method which generates three parameters (Angle, Magnitude, Gradient). Testing is performed on sample gait videos. The parameters are recognized through the artificial neural network (ANN) classifier. Results of analysis stages and parameters are compared to manually acquired data.

Keywords— gait analysis, HOG,ANN classifier,
Automated tracking.

I. INTRODUCTION

A. Motivation

CURRENT gait measurement methods involve complex marker systems, multiple cameras, a dedicated gait laboratory and trained personnel. This paper presents a simple single-camera system which has low processing time and is usable remote from the filming location and without the need for qualified gait analysts at the data acquisition stage. While this system is not intended to replace marker-based systems, it allows the study of gait to broaden beyond the gait laboratory while providing results comparable to those achievable with standard systems. It has been used, for example, to analyze gait in video clips filmed in another country. It is hoped that its simplicity will encourage therapists and patients to participate in gait studies and make the most of the technology available.

B. Marker-Based Systems

Marker-based systems are still the most reliable and widely used. However, they require specific equipment and expertise, not accessible outside a gait laboratory. This can be a significant issue when patients are too unwell to travel or when large data sets are required for study. Also, as demonstrated in[1], gait facilities are not readily available to many potential users. Within a gait laboratory, marker placement is still difficult. Marker positions have a significant effect on system output.

Slight inaccuracies, particularly around the joints, can cause failure. Reliability can be improved, though this requires added cameras, added expense and restriction to a fixed filming location. Passive marker systems are less intrusive than active but require more markers to compensate for vulnerability to occlusion [2]. This happens during walking as the subject's arms swing back and forth, occluding the pelvic region. Many studies on trends in gait analysis, e.g., [3], have predicted that future developments in gait analysis will tend away from marker-base systems.

C. Marker-Free Gait Analysis

Many research groups are striving to develop the first fully automated marker-free gait analysis system. There are already some commercially available marker-free motion capture systems, e.g., [4]. To date however, none is completely automated and all require a gait laboratory environment, several measurements of the subject and/or manual intervention at various stages. These systems sometimes suffice, but have not been readily embraced by therapists as an alternative to marker-based systems in monitoring pathological gait. Some portable gait measurement systems are available, e.g., [5] and [6], but these concentrate on velocity measurements and do not acquire full kinematics. Here, this task is tackled using computer vision based techniques. The greatest challenge for computer vision lies in analysis of the lower limbs in the

ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 4, Special Issue 19, April 2017

sagittal plane. The difficulties in the sagittal plane stem from the similarity and proximity of the two legs and from speed change during the swing phase. Many attempts at marker-free systems have been based on feature detection and tracking or on apparent motion [8]. However, on crossover of the legs, during swing, image features become less well defined and it is difficult to identify any apparent motion. Although this is not technically occlusion, the result is the same: tracking cues are lost. As the legs cross, the image of the moving leg becomes blurred and indistinguishable from the stationary leg. With standard techniques, this can lead to motion vectors having erroneous zero values. Marker-free techniques are still being investigated in this area. Review paper [9] looks at the various tasks involved in motion analysis of the human body from a computer vision perspective and discusses recognition of human activities from image sequences. Survey [10] presents recent developments, focusing on whole-body motion and discussing various methodologies. These reviews should be consulted for a thorough summary of current research.

D. Design Goals

With patients and therapists in mind, the following goals we reset for this design.

• The system must be completely automated
• The system must be simple to use, requiring minimal training.
• The output will be a comprehensive set of sagittal plane gait graphs and parameters, sufficiently accurate for clinical diagnosis.
• The input will be a single video file of the patient walking.
• The gait video can be filmed in any reasonable environment without significant restrictions.
• The subject can be fully and appropriately clothed.
• The subject can walk freely.

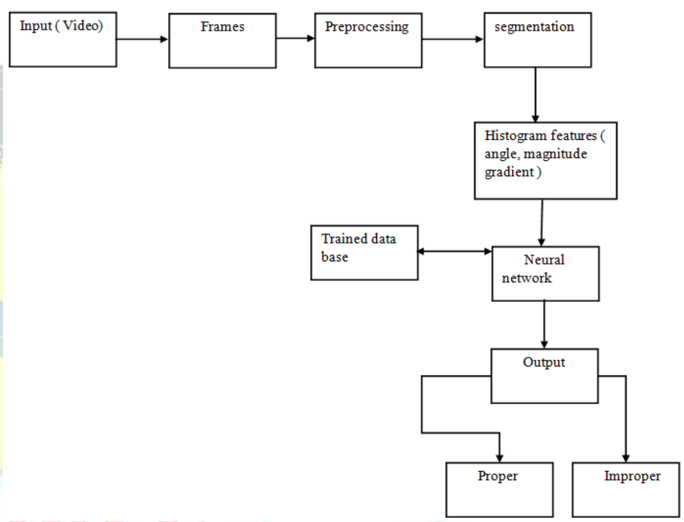
While accuracy is important, this design is intended as a first stop gait measurement system and is not intended, at this stage, to compete with marker-based systems in terms of accuracy. In addition, because of the specific application, expectations are restricted to the following.

• It is reasonable to expect adequate lighting and contrast in the filming environment.
• The data will be filmed from a stationary camera.
• The subject will walk approximately fronto -parallel to the camera.
• The subject will be fully visible in all frames from head totoe.
• Clothing will not hide the subject's leg outline, for example,skirts may not be worn.
• The height of the subject known.

II.SYSTEM DESIGN:

A. SYSTEM MODEL:

BLOCK DIAGRAM:



B. PRE PROCESSING:

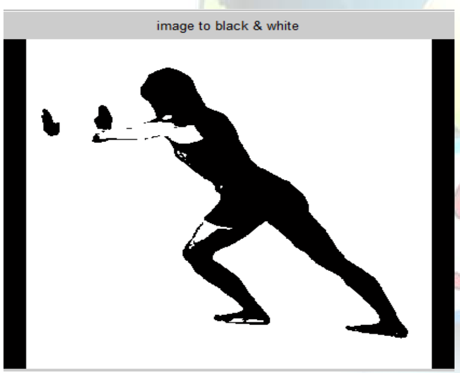
The frame work of the system starts with the acquiring of video images by means of camera and pre-processing has to be done on them for enhancing the quality of frames in the sequences. The video frames have a lot of noise due to camera, illumination and reflections etc. This can be removed and quality of images can be enhanced with the help of preprocessing stages.

ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 4, Special Issue 19, April 2017

C.SEGMENTATION:

In fitting the model, it is assumed that the region being modeledis clearly defined and outlined. Therefore, a method of segmenting the region being modeled from the rest of the imagemust be designed. Many moving images can be segmented intoareas of coherent motion and these modeled as independentlymoving objects. However, human bodies consist of parts thatare not only similar in appearance but also similar in movementand position, making them difficult to separate. In addition, individualsegments do not move independently but are connectedand affect each other's motion. This problem is most exaggeratedin the lower limbs where the moving parts on the leg beingtracked have counterparts on the other leg. The two legs are generallyvery similar in appearance and texture and so there may be little or no apparent change in the image as they move in front of one another. Particularly at crossover, the outline can be blurred and significant edges lost.



Many method are there for achieving segmentation, However, a method fuzzy clustering is used. Fuzzy image processing has three main stages, namely image fuzzification, modification of membership values and if necessary image defuzzification.

In fuzzy means clustering every point has a degree of belonging to clusters, as in fuzzy logic, rather than belonging completely to just one cluster. Thus points on the edge of a cluster. The FCM algorithm is one of the most widely used fuzzy clustering algorithm which attempts to partition a finite collection of elements x=(…..) , into a collection of fuzzy clusters with respect to some criterion. The following objective function is,

III. IMPLEMENTATION:

Histograms of Oriented

Gradients

1. Objectives

Histogram of Oriented Gradient descriptors, or **HOG** descriptors, are feature descriptors used in computer vision and image processing for the purpose of object detection. The technique counts occurrences of gradient orientation in localized portions of an image. The purpose of this lab is to implement the algorithm of extracting Histogram of Gradient Orientation (HOG) features. These features will be used then for classification and object recognition.

2. Algorithm Implementation

A.Gradient Computation

The first step of calculation is the computation of the gradient values. The most common method is to apply the 1D centered point discrete derivative mask in both the horizontal and vertical directions. Specifically, this method requires filtering the grayscale image with the following filter kernels:

$$D_x = [-1\ 0\ 1] \text{ and } D_y = [1\ 0\ -1]$$

B.Orientation Binning:

The second step of calculation involves creating the cell histograms. Each pixel within the cell casts a **weighted vote** for an orientation-based histogram channel based on the values found in the gradient computation. The cells themselves are rectangular and the histogram channels are evenly spread over 0 to 180 degrees or 0 to 360 degrees, depending on whether the gradient is "unsigned" or "signed". Dalal and Triggs found that unsigned gradients used in conjunction with 9 histogram channels performed best in their experiments. As for the vote weight, pixel contributioncanbethegradientmagnitudeitself or the square root or square of the gradient magnitude.

ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 4, Special Issue 19, April 2017

C. Descriptor Blocks:

In order to account for changes in illumination and contrast, the gradient strengths must be locally normalized. Which requires grouping the cells together into paper, spatially connected blocks. These blocks typically overlap meaning that each cell contributes more than once to the final descriptor. Two main block geometries exists: Rectangular R-HOG blocks and circular blocks C-HOG. R-HOG blocks are generally square grids, represented by three parameters the number of cells per block. The number of channels per cell histogram. [7] proposed a system in which the cross-diamond search algorithm employs two diamond search patterns (a large and small) and a halfway-stop technique. It finds small motion vectors with fewer search points than the DS algorithm while maintaining similar or even better search quality. The efficient Three Step Search (E3SS) algorithm requires less computation and performs better in terms of PSNR.

3. ARTIFICIAL NEURAL NETWORK (ANN):

• The neural network is to consider the last layer as a logistic regression classifier.

• The hidden layers can be thought of as automatic "feature selectors". This eliminates the work of manually choosing the correct number of, and power of, the input features.

•Thus, the ANN becomes an automatic power feature selector and can find any linear or non-linear relationship or serve as a classifier of arbitrarily complex sets. It is typically defined by three types of parameters, they are, the interconnection pattern between the different layers of neurons, the weights of the interconnections, which are updated in the learning process, the activation function that converts a neuron's weighted input to its output activation.

IV.RESULTS:

A) Visual Results:

Visual data are useful for gauging the success of the algorithmand could be used to create an avatar to mimic gait in avirtual environment. This is a very tangible form of output but isonly fully realizable with complete 3-D gait data, i.e., includingtransverse and coronal planes of movement and pelvis and ankledata. Here, focus is on the sagittal plane and particularly on themain lower limb area, as this is the most challenging region inthe acquisition of gait information.

The figure shows the three parameters which is calculated by hog algorithm they are: Angle, Magnitude, and Gradient.

	Clip number:				
	1	2	3	4	
Subject's Height	175	180	185	166	cm
Walking Velocity	127	136	131	141	cm/sec
Stride Length	175	170	191	133	cm
Cadence	87	96	82	127	steps/min

TABLE I GAIT PARAMETERS ACQUIRED FROM THE FOUR
VIDEO SEQUENCES

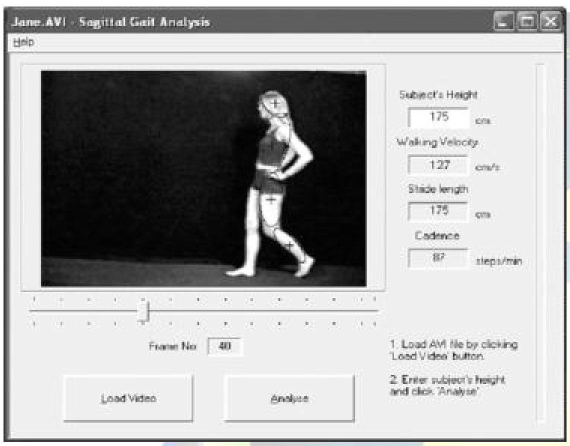


Fig: Simple user-friendly interface.

A simple user interface has been designed and demonstratesthe ease of use of the system. This is seen in Fig. Along withvisual and graphical results, significant gait parameters are normallyacquired. These are walking velocity, stride length and cadence.

V. DISCUSSION:

Few commercial marker-free systems are in current use ingait analysis. They are becoming more common in areas suchas sports science, animation and surveillance but the accuracyand detail required for gait analysis makes system designchallenging. The greatest obstacles to visual systems such asmarker-free systems lie in sagittal-plane acquisition. Thus, thiswork focuses on designing a reliable marker-free system formonitoring sagittal-plane movement in the gait cycle.

This system will allow patients' gait to be recorded in a relaxedand convenient environment without the need for a trainedtherapist to be present. Thus, therapists can use their expertiseto diagnose and treat gait rather than spending time masteringand using marker systems. This system will be used in the NationalRehabilitation Hospital, Dublin where it was developed,and will become part of a more complete gait laboratory designin the future.

VI. ACKNOWLEDGMENT

The authors would like to acknowledge the National RehabilitationHospital, Dún Laoghaire, Co. Dublin, Ireland for supportand facilities. The authors would also like to thank Dr. E.Lemaire of The Rehabilitation Centre in The Ottawa Hospitaland S. Nyogi of the Massachusetts Institute of Technology.

VII.REFERENCES

[1] D. H. Sutherland, "The evolution of clinical gait analysis Part III—Kineticsand energy assessment," Gait Posture, vol. 21, pp. 447–461,
2005.

[2] J. R. W. Morris and A. Macleod, "An investigation of the sourcesand characteristics of noise in a video-based kinematic measurementsystem," Models, Connection With Experimental Apparatus and RelevantDSP Techniques for Functional Movement Analysis, DeliverableF, CAMARC (A1012) CEC/AIM Project, 1990.

[3] R. Baker, "Gait analysis methods in rehabilitation," J. Neuroeng. Rehabil.,vol. 3, p. 4, 2006.

[4] R. Frischholz and T.Wittenberg, "Computer aided visual motion analysis,"Mikromak GmbH, 2001.

[5] A. M. Sabatini, "Real-time Kalman filter applied to biomechanical datafor state estimation and numerical differentiation," Med. Biol. Eng.Comput., vol. 41, pp. 2–10, 2003.

[6] R. F. Weir and D. S. Childress, "A portable, real-time, clinical gaitvelocity analysis system," IEEE Trans. Rehabil.Eng.,vol. 5, no. 4, pp.
310–321, Dec. 1997.

[7] Christo Ananth, A.Sujitha Nandhini, A.Subha Shree, S.V.Ramyaa, J.Princess, "Fobe Algorithm for Video Processing", International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering (IJAREEIE), Vol. 3, Issue 3,March 2014 , pp 7569-7574

[8] J. Segen, "A camera-based system for tracking people in real time," inProc. 13th Int. Conf. Pattern Recognit., 1996, vol. 3, pp. 63–67.

[9] J. K. Aggarwal and Q. Cai, "Human motion analysis: A review," inProc. IEEE Nonrigid Articulated Motion Workshop, 1997, pp. 90–102.

[10] T. B. Moeslund, A. Hilton, and V. Krüger, "A survey of advances invision-based human motion capture and analysis," Comput. Vis. ImageUnderstand., vol. 104, pp. 90–126, 2006.

[11] J. Courtney, D. P. Burke, and A. M. de Paor, "Application of digitalimage processing to marker-free analysis of human gait," MeasurementSci. Rev., vol. 1, pp. 11–14, 2001.

ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 4, Special Issue 19, April 2017

[12] K. Rohr and A. K. Systeme, "Human movement analysis based on explicitmotion models," in Motion-Based Recognition, M. Shah and R.Jain, Eds. Boston, MA: Kluwer, 1997.
[13] J. Yamato, J. Ohya, and K. Ishii, "Recognizing human action in timesequentialimages using hidden Markov model," in IEEE Comput. Soc.Conf. Comput. Vis. Pattern Recognit., 1992, pp. 379–385.
[14] A. Blake and M. Isard, "The CONDENSATION algorithm—Conditional
density propagation and applications to visual tracking," Adv.Neural Inf. Process. Syst., vol. 9, p.
361, 1997.
[15] J. Deutscher, A. Blake, and I. Reid, "Articulated body motion captureby annealed particle filtering," in IEEE Conf. Comput. Vis. PatternRecognit., 2000,
vol. 2, pp. 126–133.
460