31st Annual International Conference of the IEEE EMBS
Minneapolis, Minnesota, USA, September 2-6, 2009

Investigation of Gait Features for Stability and Risk Identification in Elders

Jun Liang, Carmen C. Abbott, Marjorie Skubic, *Member, IEEE*, and James Keller, *Fellow, IEEE*

Abstract—**Today, eldercare demands a greater degree of versatility in healthcare. Automatic monitoring devices and sensors are under development to help senior citizens achieve greater autonomy, and, as situations arise, alert healthcare providers. In this paper, we study gait patterns based on extracted silhouettes from image sequences. Three features are investigated through two different image capture perspectives: shoulder level, spinal incline, and silhouette centroid. Through the evaluation of fourteen image sequences representing a range of healthy to frail gait styles, features are extracted and compared to validation results using a Vicon motion capture system. The results obtained show promise for future studies that can increase both the accuracy of feature extraction and pragmatism of machine monitoring for at-risk elders.**

I. INTRODUCTION

Research regarding silhouette-based gait and activity recognition has been fruitful in recent years. One of the most recent projects is the HumanID Gait Challenge established by DARPA [1],[2]. The project is meant for identification of individuals solely based on their walking patterns. Many different approaches have been taken to tackle the problem of extracting distinctive gait features. Space of probability functions have been shown to distinguish people in video frames regardless of the viewing angle [1]. Hidden Markov Models (HMMs) have also been in development to distinguish activity patterns not just in walking, standing, and other normal postures, but also in abnormal activity situations such as opening doors [3]. The robust model (in)validation approach has been used to classify gaits, based on a family of nominal gaits [4]. Of course, modeling has its deficiencies in that it requires a set of training data that must encompass as much of the expected postures as possible. Shape analysis and feature extraction have also been done to extract gait information. Through silhouette images, the Kendall definition of shape has been applied to make individual identification. From viewing angles of less than 22.5 degrees, classification is able to achieve 85 percent accuracy [5].

From a health care perspective, studies have been done to computationally detect the health problems in the aging subjects. Motion capture systems are used to accurately locate the specific anatomic parts involved in gait. Osteoarthritis has been studied using a six-camera Vicon motion capture system. Four reflective markers are placed around the knee joint to calculate angular acceleration and momentum [6]. In another study conducted by the Victoria University in Australia, a PEAK motion capture system is used. Unlike the 3-D Vicon, PEAK tracks reflective markers in 2-D image space. In this study, support vector machines are used to assess gait deterioration. Using the PEAK data from reflectors on legs and feet, minimum foot clearance is graphed and histograms have been shown to extract gait information [7].

Work has been done in using image silhouettes for activity recognition in the home environment. A bank of multiple HMMs has been used to model activities of daily living [8]. It has been shown that specific gait features can be extracted from silhouette data. Static information such as stride length and body height is complemented by kinematic information established by the angle of lower limb joints [9].

Our research tries to further the investigation of gait feature extraction and evaluation. Few studies have been done to investigate the gait of people who suffer from various effects of aging using image silhouettes. From interviews with residents from the TigerPlace retirement community in Columbia, MO, many voice their concerns over falls. Research has been done on developing technology to promptly and accurately detect falls. Gyroscopes and accelerometers have been used for such a task [10]. However, subjects are required to wear such equipment in order for falls to be detected. The purpose of this project is to use the technology from previous gait identification studies to assess the problematic gaits of the elderly. We seek to identify deteriorating gaits early, therefore alerting healthcare providers to more closely monitor at-risk residents.

The rest of the paper is organized as follows. Section II describes the methodology behind each of the three features extracted from the image sequences. In Section III, results obtained from the features are described with graphs presented. Finally, Section IV includes concluding words and possibilities for future work.

II. METHODOLOGY

The study began with an interest in trying to allow machines to make similar judgments as health care professionals when simply assessing the stability of the walks of individuals.

The features considered for this study are derived from a panel of nurses, physicians, and physical therapists. The panel examined the walks of volunteer residents at Tiger Place and ranked their gait stability based on certain features. Three of the features they used have been deemed possible for automatic extraction: shoulder level, back hunch, and total body movement. In this paper, we present

Manuscript received April 7, 2009. This work was supported in part by the National Science Foundation Grant IIS-0428420.

J. Liang is with Dartmouth College, Hanover, NH 03755. C. Abbott is with the Physical Therapy Department, University of Missouri, Columbia, MO 65211. M. Skubic and J. Keller are with the Electrical and Computer Engineering Department, University of Missouri, Columbia, MO 65211. Correspondence: skubicm@missouri.edu.

an investigation of these gait features. Although the work is motivated by gait data on elderly volunteers, in this preliminary work, we have collected data in the lab on healthy subjects and an experienced physical therapist who can demonstrate abnormal gait patterns.

A. Shoulder Level

The shoulder level of the subject is compared with the horizontal axis. The idea is to determine how much the subject sways from side to side by calculating the angle between his/her shoulder and the horizontal axis. Silhouette figures of the subjects are first extracted from each walking sequence. The main distribution vector of the silhouette in each frame is found through the eigenvector of the covariance matrix of the silhouette pixel coordinate matrix. The perpendicular vector to the distribution vector is assumed to be the shoulder level.

Normally, only the upper body should be used to calculate a feature such as shoulder level. However, due to the foreshortening of the camera, the silhouettes produced in the frames where the subject is further away are usually poor in definition. To divide the silhouette into two halves would further ruin the results. Thus, the distribution vector represents the entire subject.

In image space, sets of horizontal axes are defined to provide a comparison for the computed shoulder vectors. For the Fire-i cameras, the lensing effect sometimes distorts the true evaluation of the shoulder level of the subject. To solve this problem, a system of variable position axes is used. A presumably healthy subject walks through the lab environment where the data is collected. The shoulder level of the healthy subject is then manually extracted from the image frame at every location of the walk. This set of "healthy" shoulder levels is set as horizontal axes. When analyzing the test walks, the closest horizontal axis to the subject silhouette in image space is used for comparison. Treating both the horizontal axis and the calculated shoulder level as unit vectors, the angle between the variable horizontal axis and the calculated shoulder level is then found by taking the inverse cosine of the dot product between the two vectors.

B. Spinal Incline

Similar to the method used in shoulder level detection, the distribution vector of the silhouette in each frame is found. This vector represents the direction of lean of the silhouette; therefore, it works well in reflecting the general incline of the subject's spine. Unlike the shoulder level detection method, the silhouette coordinate matrix used in calculating the spinal incline consists only of the pixels in the upper body of the subject. This is because in the profile view frames, the subject moves horizontally across the frame, thus retaining a good amount of pixel definition in the silhouettes. To separate the upper body from the rest of the silhouette, a box is mapped onto the silhouette based on the vertical and horizontal minimum and maximum of the extracted silhouette. The torso takes up roughly 52 percent of the height of the silhouette [11]. Thus, the box is divided according to this ratio. See Fig. 1.

Again, due to lensing effect, another system of variable positioned vertical axes is used based on the spinal incline of a healthy subject. The angle between the vertical axis and the calculated spinal incline is found.

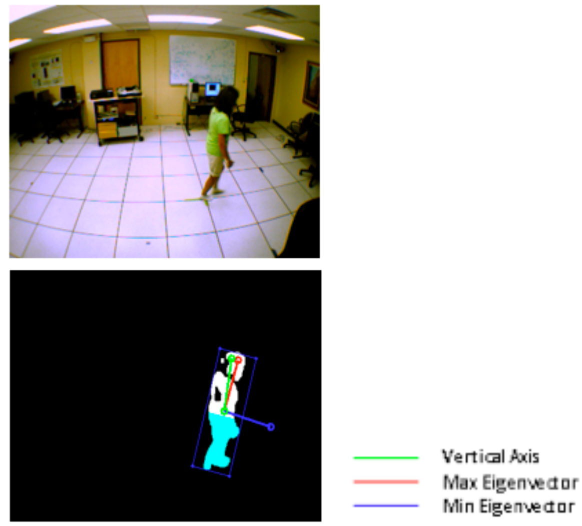

Fig.1. The blue box maps the size of the silhouette. The white portion represents the torso. The distribution vector (red) clearly deviates from the vertical axis (green).

C. Silhouette Centroid

To track total body movement, we use the silhouette centroid. The strategy is to follow our subject through the walk, and determine the degree of oscillation around the straight path of walk. See Fig. 2.

The centroid is found by averaging the coordinates of all the pixels in the silhouette. This method lessens the effect of background noise in the silhouette. To discern the degree of oscillation through the course of the walk, the least mean square error of the location of the silhouette centroid is calculated.

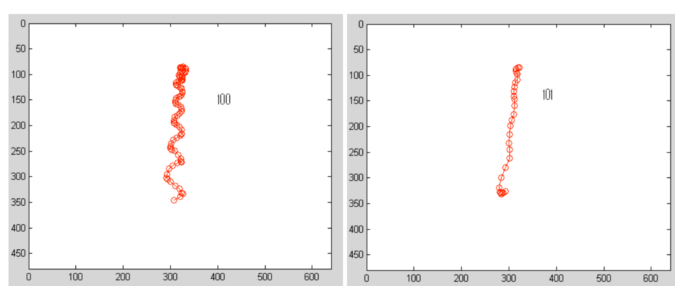

Fig. 2. Silhouette centroid during a straight walk. The subject on the left has a noticeable limp.

III. RESULTS & VALIDATION

The data are collected in two laboratories, one equipped with a seven camera VICON Motion Capture System, and one without. A total of fourteen image sequences are used to process these three features. Seven sequences are captured from the full view perspective, and seven from the profile view. Unibrain Fire-i digital cameras are used in data capture as an example of the type of low cost equipment that could be implemented in practice. Sequences 100, 101, 103, and 104 are conducted by the same person, sequences 102 and 105 are conducted by the same person, and sequences 107 to 114 are conducted by the same person (a physical therapist who has extensive experience in eldercare and can mimic gait problems). See Table I for the description of each walk.

TABLE I

Sequence ID #	Walk Pattern Description
100	Limping (full view)
103	Limping (profile view)
101	Healthy (full view)
104	Healthy (profile view)
102	Limping (full view)
105	Limping (profile view)
107	Healthy (full view)
108	Healthy (profile view)
109	Mimicked aging (full view)
110	Mimicked aging (profile view)
111	Mimicked limping (full view)
112	Mimicked limping (profile view)
113	Mimicked Parkinson's Disease (full view)
114	Mimicked Parkinson's Disease (profile view)

Each sequence contains one visible subject, which enables easy silhouette extraction using a Gaussian mixture model [12]. For the full view frames, the shoulder level and silhouette centroid are extracted. Shoulder level can only be seen clearly from the front, and the subject's side-to-side oscillation is bettered viewed from the front as well. For the profile view frames, the spinal incline is extracted. Because the eigenvectors calculated from the silhouettes depend strongly on the quality of the silhouettes, sometimes, usually due to the foreshortening of the camera, the silhouette is poor in quality and leads to inaccurate calculations. To account for these outliers, the median of the shoulder and back angles are found to represent the central tendency of the feature.

The validation for the features calculated is done through two different methods. For sequences numbered 107 to 114, the capture environment contains a seven-camera 3-D VICON Motion Capture System, which we used to validate the same set of features as the silhouette-based algorithms. Six reflective markers are placed on the subject during these eight sequences: one on each shoulder, two along the spine (at Cervical 7 and Thoracic 12), and one on each knee. A set of horizontal and vertical axes has been defined in the capture volume. The shoulder vector is determined by the position of the two markers on the shoulders, and the spinal incline is determined by the two markers along the spine. The body centroid is calculated by taking the average of the coordinates of the six markers.

For sequences numbered 100 to 105, the VICON system is not available in the capture environment. Thus, the validation is done manually. In each image frame, thirteen joints are picked from the subject. The joints are located as such: one on each shoulder, one on each elbow, one on each hand, one on the back of the neck (at Cervical 1), one on the middle of the back (at Intervertebral Disc), one on the lower back (at Lumbar 5), one on each knee,and one on each foot. Because this method of validation is also affected by the lensing effect, variable position axes are used here as well. The shoulder vector is determined by the two shoulder joints, the spinal incline is determined by Cervical 1 and Lumbar 5, and the body centroid is the average of the coordinates of the thirteen joints. The experimental results and validation are shown in Tables II, III, and IV.

TABLE II
SHOULDER LEVEL

Sequence ID #	Description	Shoulder Level Horizontal Angle Variance (silhouette model)	Shoulder Level Horizontal Angle Variance (validation model)
100	Limping	11.88°	0.02°
101	Healthy	11.335°	0.003°
102	Limping	4.83°	0.003°
107	Healthy	7.04°	16.74°
109	Aging	5.04°	13.15°
111	Limping	4.19°	7.17°
113	Parkinson's Disease	8.86°	8.15°

TABLE III
SPINAL INCLINE

Sequence ID #	Description	Spinal Incline Vertical Angle Median (silhouette model)	Spinal Incline Vertical Angle Median (validation model)
103	Limping	14.83°	7.96°
104	Healthy	4.05°	0.57°
105	Limping	18.09°	17.67°
108	Healthy	3.09°	3.45°
110	Aging	7.32°	6.88°
112	Limping	7.00°	6.62°
114	Parkinson's Disease	19.21°	20.67°

TABLE IV
SILHOUETTE CENTROID

Sequence ID #	Description	Silhouette Centroid LMS Error (pixel)	Validation Centroid LMS Error (pixel)	Validation Centroid Orthogonal Distance (unit in space) [13]
100	Limping	4376	5543	--
101	Healthy	565	915	--
102	Limping	4520	5652	--
107	Healthy	1354	--	2160
109	Aging	1540	--	2420
111	Limping	916	--	1970
113	Parkinson's Disease	203	--	1660

In Table II, the variance of the shoulder level is calculated instead of central tendency statistics because it reflects not only how much the subject is leaning to one side but also how much the subject sways from side to side. The numerical results from this feature are not reflective of the quality of the subject's walk. Spinal incline results, however, show more promise. The limping, aging, and Parkinson's disease sequences all demonstrate more deviation from the vertical axis than the healthy sequences. This finding through silhouette analysis is confirmed by the validation model. In fact, the experimental value error for the spinal incline angle is only 7.45%. Silhouette centroid tracking yields equally promising results. From Table IV, we see that limping and aging subjects' centroids show the highest degree of oscillation around the line of best fit. The only exception appears in sequence 111, where both the silhouette centroid LMS error and its validation centroid orthogonal distance are lower than those of the healthy sequence 107. However, the general trend provides a measure to distinguish, to a certain degree, healthy subjects from those with health problems. Subjects with too much oscillation from side to side likely have instability in their legs, causing them to sway from side to side. A person walking with too little side-to-side oscillation likely suffers from Parkinson's disease, which symptoms include rigid body posture, causing the patient to proceed in a hopping fashion down a straight line [14]. The values obtained here are for comparative purposes, with the healthy subjects setting the standard. With more data, a set of thresholds may be developed that will automatically classify a subject into a particular category based on his/her silhouette centroid oscillations.

IV. Future Work

The features reported here are still in the developmental stage. These initial experimental results show that it is possible to automatically extract these features based solely on the image frames of subjects and the results obtained are promising. Further trials need to be conducted on actual patients of problem gaits. Then, we will be able to establish specific models and threshold values in each feature that will enable the system to automatically separate the subjects into categories of healthy, limping, Parkinson's disease, etc. It is important to realize, however, some limitations to these features reside in the fact that the silhouettes extracted from these sequences use a method that places greater emphasis on speed rather than the intricacies of post processing. Therefore, background noise could have affected the results, especially in the frames where foreshortening causes the subject to appear very small. With better silhouettes, we may be able to refine these calculations and extract more detailed features such as step size and bend at the knee to build a more complete profile for the subjects.

The ultimate goal is to install inexpensive cameras, such as the Unibrain, in the homes of elderly residents. Using the silhouettes extracted from the images captured, an automated and noninvasive system can then identify residents with developing gait problems and alert the healthcare providers early to more closely monitor these residents to prevent them from falling.

References

[1] Vega, Isidro R., and Sudeep Sarkar. "Statistical Motion Model Based on the Change of Feature Relationships: Human Gait-Based Recognition." *IEEE Transactions on Pattern Analysis and Machine Intelligence,* vol. 25, 2003, pp. 1323-328.

[2] Wang, Liang, Tieniu Tan, Huazhong Ning, and Weiming Hu. "Silhouette Analysis-Based Gait Recognition for Human Identification." *IEEE Transactions on Pattern Analysis and Machine Intelligence,* vol. 25, 2003, pp. 1505-518.

[3] Wang, Ying, Kaiqi Huang, and Tieniu Tan. "Abnormal Activity Recognition in Office Based On R Transform." *Proc. of the International Conference on Image Processing*, 2007, pp. 341-44.

[4] Mazzaro, Maria C., Mario Sznaier, and Octavia Camps. "A Model (In)Validation Approach to Gait Classification." *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 27, 2005, pp. 1820-825.

[5] Veeraraghavan, Ashok, Amit K. Roy-Chowdhury, and Rama Chellappa. "Matching Shape Sequences in Video with Applications in Human Movement Analysis." *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 27, 2005, pp. 1896-909.

[6] Turcot, Katia, Rachid Aissaoui, Karine Boivin, Michel Pelletier, Nicola Hagemeister, and Jacques A. De Guise. "New Accelerometric Method to Discriminate Between Asymptomatic Subjects and Patients with Medial Knee Osteoarthritis during 3-D Gait." *IEEE Transactions of Biomedical Engineering*, vol. 55, 2008, pp. 1415-422.

[7] Begg, Rezaul K., Marimuthu Palaniswami, and Brendan Owen. "Support Vector Machines for Automated Gait Classification." *IEEE Transactions of Biomedical Engineering*, vol. 52, 2005, pp. 828-38.

[8] Park, Sangho, and Henry Kautz. "Privacy-preserving Recognition of Activities in Daily Living from Multi-view Silhouettes and RFID-based Training." Technical Report, 2008 AAAI Fall Symposium, Arlington, Virginia, 2008. 70-77.

[9] Su, Han, and Feng-Gang Huang. "Human Gait Recognition Based on Motion Analysis." *Proc. of the Fourth International Conference on Machine Learning and Cybernetics,* 2005, pp. 4464-468.

[10] Li, Qiang, John A. Stankovic, Mark Hanson, Adam Barth, and John Lach. "Accurate, Fast Fall Detection Using Gyroscopes and Accelerometer-Derived Posture Information." *Proc. Of Body Sensor Networks*, Berkeley, CA.

[11] Kumar, Shrawan, ed. *Biomechanics in Ergonomics*. New York: Taylor & Francis Group, 1999. Google Book Search. 14 Aug. 2008. P. 311.

[12] Stauffer, Chris, and W. Eric L. Grimson. "Learning Patterns of Activity Using Real-Time Tracking." *IEEE Transactions on Pattern Analysis and Machine Intelligence,* vol. 22, 2000, pp. 747-57.

[13] Petras, Ivo, and Igor Podlubny. "Orthogonal Linear Regression in 3D-space by Using Principle Components Analysis," Program documentation. Matlab Central, 2006. Retrieved Aug. 7, 2008 <http://www.mathworks.com/matlabcentral/fileexchange/12395>.

[14] "Symptoms." *Parkinson's Disease*, 2008. Mayo Clinic. Retrieved Sept. 4, 2008 <http://www.mayoclinic.com/health/parkinsons-disease/ds00295/dsection=symptoms>.