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Exploiting Visual Cues for Learning Gait Patterns Associated with Neurological Disorders

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Graphical abstract
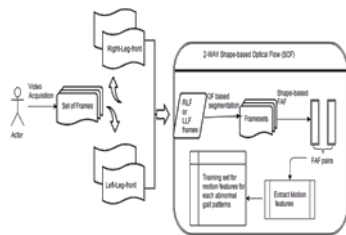
Abstract

Records of cases involving neurological disorders often exhibit abnormalities in the gait pattern of an individual. As mentioned in various articles, the causes of various gait disorders can be attributed to neurological disorders. Hence analysis of gait abnormalities can be a key to predict the type of neurological disorders as a part of early diagnosis. A number of sensor-based measurements have aided towards quantifying the degree of abnormalities in a gait pattern. A shape oriented motion based approach has been proposed in this paper to envisage the task of classifying an abnormal gait pattern into one of the five types of gait viz. Parkinsonian, Scissor, Spastic, Steppage and Normal gait. The motion and shape features for two cases viz. right-leg-front and left-leg-front will be taken into account. Experimental results of application on real-time videos suggest the reliability of the proposed method.

Keywords: Optical Flow, Neurological Disorders, Moments, Fourier Descriptor

1.0 INTRODUCTION

Gait has been defined as coordinated cyclic combination of movements resulting in human locomotion [1] [2]. Motions occur in a coordinated and cyclic manner thereby making gait an excellent biometric. Examples of gait are walking, jogging, climbing steps and so on. Gait possesses a potential to recognize individuals at a distance and at a low resolution, mostly in surveillance areas where other biometrics such as fingerprint and iris recognition cannot play the role. Joseph H. Friedman in his article entitled "Gait disorders in the Elderly" defines a normal gait as: "My own interpretation of Normal is that it would not stand out as different if I saw the person walking on the street, or in a crowd" [3]. On the other hand, disordered gait has been defined as a slowed or aesthetically abnormal gait either as a result of age-associated diseases or neurological and non-neurologic disorders [4]. According to the article entitled "MedlinePlus" by NIH the causes of specific

gait patterns, for example, propulsive gait, are carbon monoxide poisoning and Parkinson's disease; spastic gait are brain or head trauma, brain tumor and cerebral palsy; steppage gait, are caused by multiple sclerosis, spinal cord injury [5]. According to the literature, three approaches for abnormal gait analysis are image processing, floor sensors and sensors placed on body. This study focuses on exploiting visual cues associated with abnormalities of certain gait patterns under training and testing paradigm. Aspects of abnormality in gait patterns [3] include:

- stand: ability to get up from chair and stand-up
- posture
- stride Length: distance between steps
- arm swing
- base: distance between feet during walking
- speed: normal, slow or increased
- turning: unlike normal gait (pivoting while turning) other people with disorders take several steps while turning

- balance-assessment: patient should walk in a straight line

Assessment of neurological disorders highly relies on the experience of a neurologist. Video being a pervasive media type has made computer-vision based analysis of human activities indispensable. Literature reports two kinds of image processing techniques to enable accurate quantitative measurements [12]. One involves setting of body attachments such as motion marker systems, whereas the other technique involves automatic analysis from the visual cues extracted from a video captured under a simple setting. Meanwhile, rapid progresses in image acquisition technologies, machine learning technologies have satisfied the learning requirements of gait patterns and provide an efficient basis for other novel approaches. The influx of ample amount of research in gait analysis is mostly associated to identifying tasks or getting an idea of the well-being of an individual by classifying the gait as normal or abnormal. The current work takes analysis of abnormal gait patterns one step ahead by classifying the abnormal gait patterns into five different gait patterns: normal gait, parkinsonian gait, scissor gait, spastic gait, steppage gait. Among the broad spectrum of methods proposed for gait analysis, notable methods broadly fall under silhouette-based method and shape-based method. On the other hand, pattern recognition can be aided by either hand-crafted complex features extracted from images and video sequences or by view-based approaches [7]. We observed a lack of use of such view-based paradigms in classification of abnormal gait patterns associated with neurological disorders. Therefore a machine vision-based methodology has been used to envisage the classification of abnormal gait patterns. Research on human gait analysis marks its inception in 19th century which revolved around a quantitative aspect. Such research involved measurement of different parameters characterizing gait. This quantification-driven gait analysis has found ample application in the field of sports [8] [9], identification of people for security purposes [10], and medicine [11]. The current problem revolves around assessing the degree of abnormality in the gait of an individual. This incorporates an expert evaluation of patient's history subject to observation of abnormal gait patterns. Our contribution is towards a real-time analysis of abnormalities of gait patterns. This paper deals with classification of a gait pattern as either of five types based on motion and posture features. The underlying assumption is that each gait disorder possesses a certain type of pattern in terms of motion features and posture features.

1.1 Sensor-based Analysis of Gait Abnormalities

Symptoms of abnormal gait include freezing of gait, shuffling gait, small steps, etc. In [13] mean, median, coefficient of variability was calculated from readings taken manually by placing ultrathin force sensitive switches inside each subject's shoe. In [14] temporal distance measures like velocity, cadence, step length, stride length using ink footprint records were considered. An ambulatory gait analysis enabled by the usage of a Physilog portable data logger was carried by each subject measures the angular rate of the rotations of selected body segments [15]. An observation of arm swing, trunk and lower limb led to a four-point scale with a scale of normal, mild, moderate, severe and was tested on patients from the Rivermead Rehabilitation Centre (RRC) [16]. Data analysis resulting in force-time diagram, were conducted on 50 Normal and 150 patients with various forms of gait disturbance [17]. A web search for research articles related to "gait" reports more than 3,400 publications between 2012 and 2013. Out of 3,400 publications, 40% were related to non-wearable systems, 37.5% dealt with inertial sensor-based systems, the remaining 22.5% were related to wearable systems [18]. An observation-based and quantitative system for assessing gait abnormalities considers few general parameters such as velocity, short step length, long step length, cadence, gait autonomy, duration of stops, momentum and forces, ground reaction force and other parameters. Alvaro Muro *et al.* [18] discussed two broad categories of techniques involved in observation of gait patterns viz. semi-subjective analysis (conducted in clinical conditions by a specialist) and objective monitoring techniques (use of devices to capture and measure gait-related measures). Few semi-subjective techniques include Timed 25-Foot Walk (T25-FW), Multiple Sclerosis Walking Scale (MSWS-12), Timed Get up and Go (TUG), Extra-Laboratory Gait Assessment Method (ELGAM).

In addition, objective techniques include use of several digital or analog cameras for range imaging, Time-of-Flight (ToF) systems, structured Light, Infrared Thermography (IRT), Floor sensors. Furthermore, several recent reviews have reported that the use of wearable sensors, pressure and force sensors, and inertial sensors. Other recent works include the work of Hausdorff [19], Barth [20] [22], Bonato [21].

1.2 Scales for Abnormal Gait Analysis

It has been reported in the literature that a set of functional gait and balance tasks have been applied widely to detect and quantify the abnormalities in gait pattern. A short review of the existing gait assessments are as follows [33]:

- Dynamic Gait Index (DGI): Evaluation of alterations in gait speed, head turns, clearing obstacle, climbing steps, turning.
- Emory functional ambulation profile (EFAP): Measuring time for five conditions:
  - 5-meter walk on hard floor;
  - 5-meter walk on short pile carpeted floor;
  - timed up and go
  - step over a brick and then around a trash can;

○ walk up four steps, turn around, and return (using hand rail if needed)
- Established populations for the epidemiologic studies of the elderly (EPESE) short physical performance battery (SPPB): Evaluation of

  ○ ability for maintaining stance,
  ○ time to rise from chair five times
  ○ walk eight feet at usual gait speed
- Functional obstacle course (FOC): Evaluation of subject's performance along a series of 12 simulations of functional mobility tasks or situations in home environment
- Gait abnormality rating scale (GARS): Distinguishing between fallers and non-fallers using 4-level assessment of 16 gait descriptors.
- Performance-Oriented Mobility Assessment (POMA): Assessment of balance and fall risk in adults.

1.3 Video Analysis of Gait Abnormalities

According to the literature, two types of methods were proposed viz. motion marker systems and video analysis techniques [26]. This paper revolves around the second type of technique. In [27], an image-processing based architecture was defined and implemented to analyze joint angles and swing distances for two groups of people viz. healthy control persons and patients. In [28], a continuous human motion recognition system has been proposed incorporating clone-body-model. A 3d colored body model was mapped to persons in each video frame followed by tracking of joint angles to accomplish the task of analyzing the gait patterns [29]. Neural network and fuzzy clustering algorithm have been used for training limb joint angles and swing distances that is obtained by using Hough transform [30]. The system proposed in [31] does not analyze the gait dynamics but uses motion information to extract structural characteristics; motion history image being one of the widely used techniques for the same [52]. A coupled oscillator gait model for gait modeling and analysis have been proposed in [32].

Estimation of motion intensities plays an important role in this aspect. In [23], the motion vector is computed for each of the macro-block followed by training using the absolute motion information and directional information. An activity is concluded as abnormal if the probabilities of the occurrence of feature vectors are below a threshold [24]. H. Yi *et al*. [25] incorporated the concept of Pixel Change Ratio Map histogram to obtain information regarding the intensity of the motion across the video frames. A fair amount of research has been dedicated to the use of shape and motion features from video sequences as mentioned in the survey [37-46]. On the other spatiotemporal approaches, optical flow has been used for gait classification in [47-51].

Feature extraction being a crucial part of gait analysis system is largely influenced by the viewpoint.

Model-based models [57-62] have been used that deals with static body parameters like height of the silhouette, distance between head and pelvis, distance between left and right foot and maximum value of the distance between the pelvis and the feet, thigh joint trajectories, stick model, centroid of silhouette, etc. One demerit of this model-based approach is that computing of several parameters followed by searching and matching makes the process quite time-consuming. Model-free approaches [63], [40] incorporate the use of motion information without using any model parameters. Model-free approach has the advantage of faster processing but results are affected by background noise. A rich amount of computer-vision methods for gait analysis relies on human body shape and silhouettes. Although such approaches offer the merit of better tolerance to noise and short gait sequence representing one stride, they are dependent on the view angle and does not classify well for different angles other than that of training subjects. This opens up scope for proposing feature extraction methodologies for gait patters at angles other than side view.

2.0 METHODOLOGY

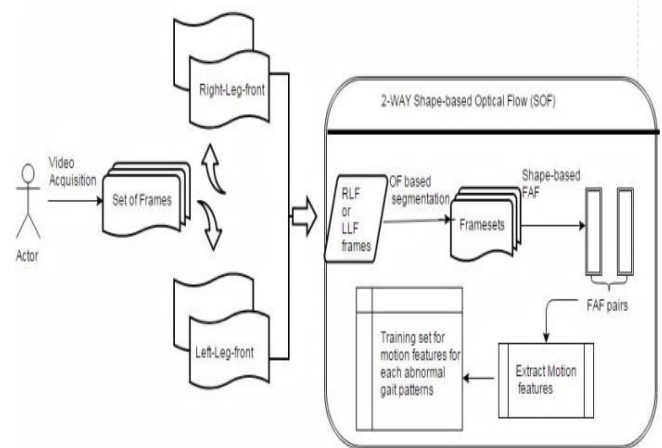Figure 1 shows the overview of the proposed system.

Figure 1 Block diagram of the processes of the system

Given a video of abnormal gait patterns the video frames are subjected to detection of human body in the frames.

2.1 Segmenting RLF and LLF

The active contour method for segmenting regions of interest on a video frame is followed by labeling each frame as either right-leg-front (RLF) or left-leg-front (LLF). This is accomplished by the position of the last white pixel starting from the bottom of a frame. An

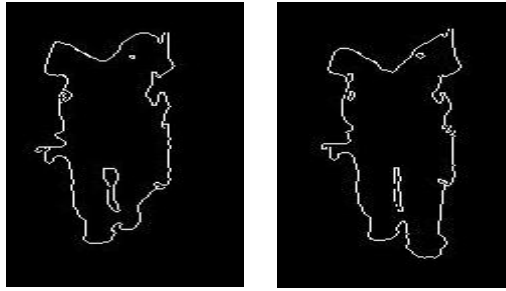example of RLF and LLF frame has been shown in Figure 2.

Figure 2 Segmented RLF and LLF frames

2.2 2-way (Shape-Optical-Flow) SOF

A method for feature extraction has been proposed in this section which is termed as 2-way SOF, the sub-modules of which are described below:

OF based grouping of frames:
Unlike other works like [12] where measurements are taken when legs are closest and farthest, this work takes under consideration the motion patterns between successive frames the captured video. The proposed system aims to classify the abnormal gait patterns from the frontal view. The samples of video taken in this work consist of video frames with the following assumptions:

- Individual coming towards the camera
- Camera is not moving.
- The individual does not change the direction of walking
- The individual walks with uniform speed

The only difference in the video frames of a single video is depths. In order to address this problem, we group the frames into framesets based on Histogram of Optical Flow feature (HOOF) [36]. HOOF features are invariant to scale and the direction in which a person is moving across the video frames. Furthermore, this method does not require background subtraction prior to feature extraction. HOOF is used to group frames with minimal depth change. Subsequently these frames are used to detect maximal shape changes in the following step.

This step is analogous to detect gait cycle prior to feature extraction for gait patterns. For model based approaches that rely on the silhouettes of subjects in side view, width of the silhouette over time is useful to analyze the peaks and valleys that represents the distance between right and left leg. However, silhouette width for frontal views provide very limited information for the same function. These drawbacks of laterally-viewed silhouettes have motivated the use of

motion cues combined with point tracking to detect gait cycle in this step.

Shape based Farthest Frame:
Silhouette based approaches for gait analysis has been effectively used by many researchers [40] [41], which definitely implied the strong cue that shape feature provides in the area of gait analysis. Furthermore, the contour images for individuals in motion for three different abnormal gait patterns are shown in Figure 3. The objective of this step is to obtain the frames with maximal shape changes in the lower region of human body. Kanamori [34] mentions that there are three methods for region-based correspondences viz., elliptical descriptor, Fourier descriptor and shape context. Fourier descriptor has been chosen in this context for assessing the difference between shapes of the lower region of a human body while walking, across video frames. The shape descriptor is computed as described in [34].

The nth Fourier coefficient for N segments, denoted by u_n (n= 0, 1,...,N-1) is computed as follows:

$$u_n = \frac{1}{N} \sum_{t=0}^{N-1} r_t \exp\left(\frac{-j2\pi nt}{N}\right)$$

Where j is imaginary unit

In order to make the shape descriptor invariant to scaling the feature vector is divided by u_0, which is dependent on scale,

$$f = \left(\frac{|u_1|}{|u_0|}, \frac{|u_2|}{|u_0|}, \ldots, \frac{|u_{N-1}|}{|u_0|} \right)$$

The pair of frames with maximal shape variation with minimal depth variation is termed as Farthest Frames (FAF).
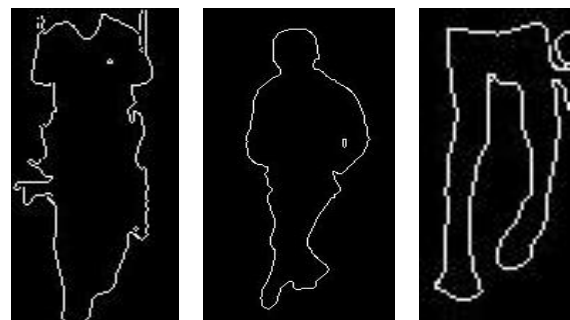

Figure 3 Contours of postures for Parkinsonian Gait, Scissor Gait, Spastic Gait

Extract motion information from Motion History Image(MHI) and Contour image:
Given the video frames with maximal shape change and minimal depth variation, the next step for feature extraction is conducted from:

MHI constructed from the FAF:

$$I_{mhi}(i,j,t) = \{ \begin{array}{l} \tau, B_{diff}(i,j,t) = 1 \\ \max(0, I_{mhi}(i,j,t-1) - \tau) \end{array}$$

Hu-moments are calculated from the MHI [35] obtained from the (N=3, FAF pair and the frame that lies between them) images belonging to a FAF as follows:

$$B_{diff}(i,j,t) = B(i,j,t) - B(i,j,t-1)$$

Where B$_{diff}$ is the binary difference image.

Where t varies from k to (k+N-1)
τ is a constant
I$_{mhi}$ is the motion history image.

Seven Hu moments are obtained from each of the motion history image that represents a set of three frames containing FAF.

Contour images belonging to each FAF:
Variational approach of optical flow estimation, as proposed by Brox [7] is followed in this step to compute the dense motion features from the images in FAF. This results in a vectored representation of a set of video frames show an individual walking towards the camera.

   Figure 4 explains the reason behind naming the proposed method as 2way- SOF. It uses a *motion* based approach for grouping frames into frameset with minimal depth. This group of frames is used to detect frames with maximal *shape* variation thereby containing FAF. These FAF are used to extract *motion-*oriented features for training the system with features of the abnormal gait types.
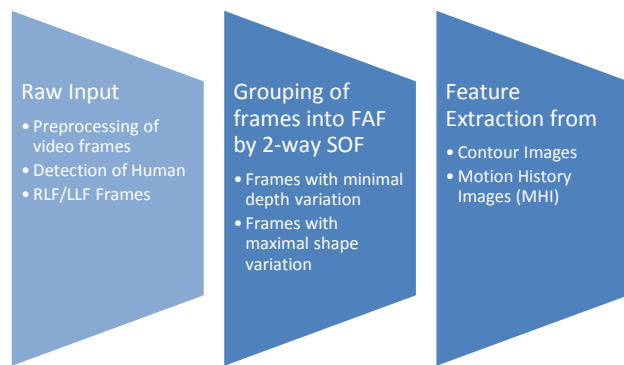

Figure 4 2-way SOF

2.3 Template Matching

Templates are created for each gait pattern based on the set of frames identified as RLF or LLF. Templates for a test gait pattern is then used to compare with each existing trained patterns of gait that have been labelled as one of the five gait patterns viz. Parkinsonian, scissor, spastic, Steppage and normal gait. The matching score is obtained by computing the correlation between train and test template vector. Let tr and ts be a train template and test template vector. Then the matching score by means of correlation is calculated as follows:

$$corr\_score = \frac{\text{cov}(tr,ts)}{\sigma_{tr}\sigma_{ts}}$$

Where, cov(tr,ts) refers to the covariance measure and σ_{tr} and σ_{ts} refers to standard deviation for train and test template.

2.4 Relationship with MHI and MEI

MHI is one of the static representations of motion occurring in a given window of time. While Motion Energy Image (MEI) incorporates only spatial information on 'where did the motion occur?' MHI entails the temporal aspect too. The proposed method in this paper can be considered as a preprocessing step for selection of the frames for construction of MHI. The steps that follow extraction of motion features from MHI images are shown in Figure 4.

3.0 RESULTS AND DISCUSSION

Table 1 shows a brief details on the video data used for classification of abnormal gait patterns. Table 2 shows the recognition results for the following gait patterns:
(G1): Parkinsonian gait
(G2): Scissor gait
(G3): Spastic gait
(G4): Steppage gait
(G5): Normal gait

Table 1 Training Data

Type of gait	Duration	Subjects Involved
Normal Gait	9.05	1
	9.21	16
	2.31	2
	10.28	4
	11.43	3
Parkinsonian Gait	2.17	2
	3.45	3
	1.08	1
Scissor Gait	00.36	1
	1.20	1
	3.21	2
Spastic Gait	00.31	2
	1.43	1
	7.53	1
Steppage Gait	00.28	1
	00.11	1
	00.43	1

Table 2 Recognition Results

Method	TL	VS	Number of frameset recognized as gait type					TPR	PL
			G1	G2	G3	G4	G5		
MHI	5	V1	1	0	0	5	14	0.7	5
		V2	3	4	0	0	13	0.6	5
EDGE	5	V1	6	1	0	1	12	0.6	5
		V2	4	4	0	2	11	0.5	5
MHI	1	V1	9	3	2	5	1	0.4	1
		V2	18	0	0	0	2	0.9	1
EDGE	1	V1	10	2	5	2	1	0.5	1
		V2	8	2	1	2	7	0.4	1
MHI	2	V1	3	5	4	6	2	0.3	4
		V2	4	12	0	0	4	0.6	2
EDGE	2	V1	7	3	1	3	6	0.2	1
		V2	8	4	0	4	4	0.2	1
MHI	2	V1	3	11	0	6	0	0.6	2
		V2	2	18	0	0	0	0.9	2
MHI	4	V1	3	2	6	9	0	0.5	4
		V2	2	5	0	6	7	0.3	5
EDGE	4	V1	6	2	0	7	5	0.4	4
		V2	4	1	0	12	3	0.6	4

List of terms used in Table 2:
    TL: True label of Gait pattern
    VS: Video sequence number
    TPR: True Positive Rate
    PL: Predicted Label of Gait pattern

20 pairs of FAFs are considered to test for five gait patterns. TPR gives the percentage of FAFs correctly recognized and PL is obtained from the label that is predicted for maximum percentage of FAF pairs. Even though the method proposed in this work does not reach above 90% accuracy in recognition of individual FAFs, this system correctly recognizes the abnormal gait pattern across a wide portion of video frames. Figure 5 shows the TPR for four types of gait.
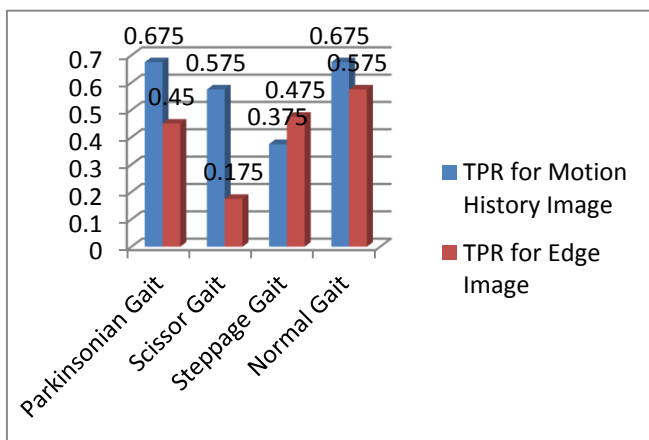

Figure 5 TPR for four types of gait on MHI and Edge images

The proposed algorithm is experimentally compared with few conventional optical flow based techniques in order to analyze the performance of the same.

3.1 Data Collection and Preprocessing

Silhouette images for six subjects from CASIA-B silhouette dataset [53] [54] has been used for feature extraction and template matching using the proposed approach and few other variational optical flow estimation techniques. Dataset B is a database of gait data captured from 11 views with 124 subjects. Each video frame provides the following information: subject id (001-124); mm: 'nm' (normal), 'cl' (in a coat) or 'bg' (with a bag); nn: sequence number; ttt: view angle ('000', '018',…,'180').

3.2 Feature Extraction and training

Given a set of video frames with silhouette images of a person walking, captured in frontal view, feature extraction for gait patterns respective to each person is accomplished by the following steps:
1. Label each frame as RLF and LLF using the method described in section 3.1.
2. Gait cycle extraction by finding frames has a maximum distance between the tips of right leg and left leg. The idea behind detecting gait cycle based on distance is driven by the fact that each gait cycle comprises of frames where the subject changes the limbs from either RLF to LLF or vice versa. It is at this point of time when the distance between the two legs is minimal across the immediate neighbor video frames.
3. For each detected gait cycle, features are extracted to be used for template matching as described in section 3.3. For performance evaluation, the proposed method is compared with optical flow features proposed by Horn and Schunck [55] (HS), Lucas and Kande [56] (PYLK) and Brox et al. [7](Brox).

3.3 Comparative Evaluation

Six subjects have been randomly chosen from 124 subjects. Only the frames under NM category has been used for performance evaluation. The True Positive rate obtained for the experiments is shown in Table 3. Results suggests that better TPR is achieved by the method proposed by Brox et al. [7] and the proposed method.

Table 3 Performance Evaluation with other optical flow estimation methods

	HS	PYLK	Brox	Shape_MHI
Sub1	0.71	1	0.65	0.73
Sub2	0.47	0.40	0.56	0.60
Sub3	0.24	0.50	0.82	0.91
Sub4	0.45	0.18	0.61	0.58
Sub5	0.33	0.88	0.84	0.82
Sub6	0.46	0.29	0.67	0.76

4.0 CONCLUSION

The factors that have not been taken into account in this study include:

1. Distance between feet while walking: This factor requires a side view of the control for such assessment.
2. Speed: Since the videos were used for training and testing in this piece of work varies in terms of framerate hence quantification of speed would not give accurate results.
3. Turning

The contribution of this study lies in the following aspects:

a. The literature has reported evaluation of functional gait tasks to measure the gait speed, time, and ability to maintain balance in order to conclude if the gait pattern is abnormal or normal. Unlike those works, this paper proposes a way whereby we can distinguish among types of gait abnormalities that can aid neurologist to predict the nature of neurological disorder the subject is likely to have.

b. Scales like GARS, POMA, TUG aims to distinguish between fallers and non-fallers. This study assumes that every subject with abnormal gait pattern bears the imbalance aspect in their walking.

c. Computer Vision algorithms has been applied in many research in order to detect abnormalities in a subject's gait pattern. The work envisaged in this paper can be posed as a step-further to detection of normal and abnormal gait for a subject whereby the class of the abnormal gait can be determined.

d. The videos used in this study differ in terms of resolution, illumination, etc. However, the features extracted and analyzed work well across videos of different characteristics. The accuracy of the system can be enhanced by increasing the number of training framesets. As the title suggests, the proposed classification framework of gait abnormalities can be used as an aid for neurologists. Therefore, this study is an attempt towards exploiting visual cues for classification of gait abnormalities.

References

[1] Boyd, J. E., and J. J. Little. 2005. Biometric Gait Recognition. *Advanced Studies in Biometrics*. Springer Berlin Heidelberg.

[2] Nixon, M. S., and J. N. Carter. 2004. On Gait As A Biometric: Progress And Prospects. *Signal Processing Conference, 2004 12th European*. 1401-1404.

[3] Friedman, J. H. 2012. Gait Disorders In The Elderly. *Medicine and Health Rhode Island*. 95(3): 84.

[4] Alexander, N. B. and A. Goldberg. 2005. Gait Disorders: Search For Multiple Causes. *Cleveland Clinic Journal Of Medicine*. 72(7): 586.

[5] http://www.nlm.nih.gov/medlineplus/ency/article/003199.htm.

[6] Dobhal, T., V. Shitole, G. Thomas, and G. Navada. 2015. Human Activity Recognition using Binary Motion Image and Deep Learning. *Procedia Computer Science*. 58: 178-185.

[7] Brox, T., A. Bruhn, N. Papenberg, and J. Weickert. 2004. High Accuracy Optical Flow Estimation Based On A Theory For Warping. *Computer Vision-ECCV 2004*. Springer Berlin Heidelberg. 25-36.

[8] Gouwanda, D., and S. M. N. A. Senanayake. 2008. Emerging Trends Of Body-Mounted Sensors In Sports And Human Gait Analysis. *4th Kuala Lumpur International Conference on Biomedical Engineering 2008*. Springer Berlin Heidelberg. 715-718.

[9] Di Stasi, S. L., D. Logerstedt, E. S. Gardinier, and L. Snyder-Mackler. 2013. Gait Patterns Differ Between ACL-Reconstructed Athletes Who Pass Return-To-Sport Criteria And Those Who Fail. *The American Journal Of Sports Medicine*. 0363546513482718.

[10] Fathima, S. M. H. S. S., and R. S. D. W. Banu. 2012. Human Gait Recognition Based On Motion Analysis Including Ankle To Foot Angle Measurement. *Computing, Electronics and Electrical Technologies (ICCEET), 2012*. 1133-1136.

[11] Sutherland, D. H. 2001. The Evolution Of Clinical Gait Analysis Part L: Kinesiological EMG. *Gait & Posture*.14(1): 61-70.

[12] Saadoon, A., and M. J. Nordin. 2015. An Automatic Human Gait Recognition System Based On Joint Angle Estimation On Silhouette Images. *Journal of Theoretical and Applied Information Technology*. 81(2): 277.

[13] Singh, M., M. Singh, and Paramjeet. 2013. Neuro-Degenerative Disease Diagnosis using Human Gait: A Review. *IJITKM*. 7(1): 16-20

[14] Holden, M. K., K. M. Gill, M. R. Magliozzi, J. Nathan, and L. Piehl-Baker. 1984. Clinical Gait Assessment In The Neurologically Impaired Reliability And Meaningfulness. *Physical Therapy*. 64(1): 35-40.

[15] Salarian, A., H. Russmann, F.J. Vingerhoets, C. Dehollain, Y. Blanc, P.R. Burkhard, and K. Aminian. 2004. Gait Assessment In Parkinson's Disease: Toward An Ambulatory System For Long-Term Monitoring. *Biomedical Engineering, IEEE Transactions on*. 51(8): 434-1443.

[16] Lord, S. E., P. W. Halligan, and D. T. Wade. 1998. Visual Gait Analysis: The Development Of A Clinical Assessment And Scale. *Clinical Rehabilitation*. 12(2): 107-119.

[17] Diehl, R. R., U. Schneider, M. Konietzko, and M. Hennerici. 1992. Quantitative Analysis Of Gait In Neurological Gait Disorders. *Posture and Gait: Control Mechanisms*.

[18] Muro-de-la-Herran, A., B. Garcia-Zapirain, and A. Mendez-Zorrilla. 2014. Gait Analysis Methods: An Overview Of Wearable And Non-Wearable Systems, Highlighting Clinical Applications. *Sensors*. 14(2): 3362-3394.

[19] Hausdorff, J. M., and N.B. Alexander. 2005. *Gait Disorders: Evaluation And Management*. Taylor & Francis US.

[20] Barth, J., M. Sunkel, K. Bergner, B. Eskofier, J. Winkler, and J. Klucken. Computer-Aided Biometric Gait And Hand Motor Skill Analysis In Parkinson's Disease. *International IZKF-Symposium on Individualized medicine*.

[21] Bonato, P., T.D. Alessio, and M. Knaflitz. 1998. A Statistical Method For The Measurement Of Muscle Activation Intervals From Surface Myoelectric Signal During Gait. *Biomedical Engineering, IEEE Transactions on*. 45(3): 287-299.

[22] Barth, J., M. Sunkel, K. Bergner, G. Schickhuber, J. Winkler, J. Klucken, and B. Eskofier. 2012. Combined Analysis Of Sensor Data From Hand And Gait Motor Function Improves Automatic Recognition Of Parkinson's Disease. *Engineering in Medicine and Biology Society (EMBC), 2012 Annual International Conference of the IEEE*. August 2012. 5122-5125.

[23] Amel, A. M., B.A. Abdessalem, and M. Abdellatif. 2010. Video Shot Boundary Detection Using Motion Activity Descriptor. arXiv preprint arXiv:1004.4605.

[24] Kiryati, N., T.R. Raviv, Y. Ivanchenko, and S. Rochel. 2008. Real-Time Abnormal Motion Detection In Surveillance

Video. *Pattern Recognition, 2008. ICPR 2008*. December 2008. 1-4.

[25] Yi, H., D. Rajan, and L.T. Chia. 2005. A New Motion Histogram To Index Motion Content In Video Segments. *Pattern Recognition Letters*. 26(9): 1221-1231.

[26] Lee, H., L. Guan, and I. Lee. 2008. Video Analysis Of Human Gait And Posture To Determine Neurological Disorders. *EURASIP Journal on Image and Video Processing*.

[27] Chang, R., L. Guan, and J. A. Burne. 2000. An Automated Form Of Video Image Analysis Applied To Classification Of Movement Disorders. *Disability and rehabilitation*. 22(1-2): 97-108.

[28] Green, R. D., and L. Guan. 2004. Quantifying And Recognizing Human Movement Patterns From Monocular Video Images-Part Ii: Applications To Biometrics. *Circuits and Systems for Video Technology, IEEE Transactions on*. 14(2): 191-198.

[29] Green, R. D., L. Guan, and J. A. Burne. 1999. Real-Time Gait Analysis For Diagnosing Movement Disorders. *Proc. SPIE. Medical Imaging*. 3338: 818-825.

[30] Tan, T., L. Guan, and J. Burne. 1999. A Real-Time Image Analysis System For Computer-Assisted Diagnosis Of Neurological Disorders. *Real-Time Imaging*. 5(4): 253-269.

[31] Wang, L., T. Tan, W. Hu, and H. Ning. 2003. Automatic Gait Recognition Based On Statistical Shape Analysis. *Image Processing, IEEE Transactions on*. 12(9): 1120-1131.

[32] Yam, C. Y., M. S. Nixon, and J. N. Carter. 2001. Extended Model-Based Automatic Gait Recognition of Walking and Running. *Proc. of 3rd Int. Conf. on Audio and Video-Based Biometric Person Authentication, AVBPA 2001*. 278-283.

[33] Alexander, N. B., and A. Goldberg. 2006. Clinical Gait And Stepping Performance Measures In Older Adults. *European Review of Aging and Physical Activity*. 3(1): 20-28.

[34] Kanamori, Y. 2013. A Comparative Study Of Region Matching Based On Shape Descriptors For Coloring Hand-Drawn Animation. *28th International Conference of Image and Vision Computing*.New Zealand (IVCNZ). 2013 .83-488.

[35] Gupta, R., A. Y. S. Chia, and D. Rajan. 2013. Human Activities Recognition Using Depth Images. *Proceedings of the 21st ACM international conference on Multimedia*. October 2013. 283-292.

[36] Chaudhry, R., A. Ravichandran, G. Hager, and R. Vidal. 2009. Histograms Of Oriented Optical Flow And Binet-Cauchy Kernels On Nonlinear Dynamical Systems For The Recognition Of Human Actions. *Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on*. 1932-1939.

[37] Little, J., and J. Boyd. 1998. Recognizing People By Their Gait: The Shape Of Motion. *Videre: Journal of Computer Vision Research*. 1(2): 1-32.

[38] Bobick, A. E., and A. Y. Johnson. 2001. Gait Recognition Using Static, Activity-Specific Parameters. *Computer Vision and Pattern Recognition, 2001. CVPR 2001. IEEE Computer Society Conference on*. 1: I-423.

[39] Luo, J., J. Zhang, C. Zi, Y. Niu, H. Tian, and C. Xiu, C. 2015. Gait Recognition Using GEI and AFDEI. *International Journal of Optics*.

[40] Han, J. and B. Bhanu. 2006. Individual Recognition Using Gait Energy Image. *IEEE PAMI*. 28(2): 316-322.

[41] Collins, R. T., R. Gross, and J. Shi. 2002. Silhouette-Based Human Identification From Body Shape And Gait. *Automatic Face and Gesture Recognition, 2002. Proceedings. Fifth IEEE International Conference on*. 366-371.

[42] Tolliver, D., and R. T. Collins. 2003. Gait Shape Estimation For Identification. *Audio-and Video-Based Biometric Person Authentication*. Springer Berlin Heidelberg. 734-742.

[43] BenAbdelkader, C., R. G. Cutler, and L. S. Davis. 2004. Gait Recognition Using Image Self-Similarity. *EURASIP Journal on Advances in Signal Processing*. 2004(4): 1-14.

[44] Kendall, D. G. 1984. Shape Manifolds, Procrustean Metrics, And Complex Projective Spaces. *Bulletin of the London Mathematical Society*. 16(2): 81-121.

[45] Boyd, J. E. 2004. Synchronization Of Oscillations For Machine Perception Of Gaits. *Computer Vision and Image Understanding*. 96(1): 35-59.

[46] Veeraraghavan, A., A. R. Chowdhury, and R. Chellappa. 2004. Role Of Shape And Kinematics In Human Movement Analysis. *Computer Vision and Pattern Recognition, 2004. CVPR 2004. Proceedings of the 2004 IEEE Computer Society Conference on*. I-730.

[47] Wang, L., H. Ning, W. Hu, and T. Tan. 2002. Gait Recognition Based On Procrustes Shape Analysis. *Image Processing. 2002. Proceedings. 2002 International Conference on*. 3: III-433.

[48] Huang, P. S., C.J. Harris, and M. S. Nixon.1999. Human Gait Recognition In Canonical Space Using Temporal Templates. *Vision, Image and Signal Processing, IEE Proceedings*. 146(2): 93-100.

[49] Lam, T. H., R. S. Lee, and D. Zhang. 2007. Human Gait Recognition By The Fusion Of Motion And Static Spatio-Temporal Templates. *Pattern Recognition*. 40(9): 2563-2573.

[50] Bashir, K., T. Xiang, S. Gong, and Q. Mary. 2009. Gait Representation Using Flow Fields. *BMVC*. September 2009. 1-11.

[51] Xiaoying, S., Z. Qiuhong, and X. Yanqun. 2010. Application Of Segmentation Based On Optical Flow For Gait Recognition. *Advanced Computer Theory and Engineering (ICACTE), 2010 3rd International Conference on*. 4: V4-567.

[52] Ahad, M. A. 2013. Motion History Image. *Motion History Images For Action Recognition And Understanding*. Springer London. 31-76.

[53] Zheng, S., J. Zhang, K. Huang, R. He, and T. Tan. 2011. *International Conference on Image Processing(ICIP)*. 2073-2076.

[54] Yu, S., D. Tan, and T. Tan. 2006. A Framework For Evaluating The Effect Of View Angle, Clothing And Carrying Condition On Gait Recognition. *18th International Conference on Pattern Recognition (ICPR'06)*. 4: 441-444.

[55] Horn, B. K., and B. G. Schunck.*1981. Determining Optical Flow. Artificial Intelligence*. 17(1-3):185-203.

[56] Lucas, B. and T. Kanade. 1981. An Iterative Image Registration Technique With An Application To Stereo Vision. *International Joint Conference on Artificial Intelligence, 1981*. 674-679.

[57] Fathima, S. S. S., R. W. Banu, and S. M. M. Roomi. 2016. Gait Based Human Recognition with Various Classifiers Using Exhaustive Angle Calculations in Model Free Approach. *Circuits and Systems*. 7(08).

[58] Cunado, D., M.S. Nixon, J.N. Carte. 2003. Automatic Extraction and Description of Human Gait Models for Recognition Purposes. *Computer and Vision Image Understanding*. 90(1): 1-41.

[59] Wagg, K., M. S. Nixon. 2004. On Automated Model-Based Extraction and Analysis of Gait. *Proc. of 6th IEEE International Conference on Automatic Face and Gesture Recognition*. 11-16.

[60] Bouchrika, I., M. S. Nixon. 2007. Modelbased Features Extraction for Gait Analysis and Recognition. *Proc. Of Mirage: Computer and Vision/Computer Graphics Collaboration Techniques and Applications*. 150-160.

[61] Niyogi, S. A., E. H. Adelson. 1994. Analyzing And Recognizing Walking Figures In XYT. *Proc. Computer Vision Pattern Recognition*. 469-474.

[62] Lee, L., W. E. L. Grimson. 2002. Gait Analysis For Recognition And Classification. *Proceedings of IEEE International Conference in Automatic Face and Gesture Recognition*. 2002. 148–155.

[63] BenAbdelkader, C., R. Cutler, R., H. L. Nanda, L. Davis. 2001. Eigen Gait: Motion based Recognition of People Using Image Self-similarity. *Proc. Of International Conference Audio and Video-Based Person Authentication*. 284-294.