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Wearable Technology for Evaluation of Risk of Falls

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***Abstract*- One's risk of fall can be quantified in terms of variability in one's gait, reflecting a loss of automatic rhythm of one's gait. In gait analysis, variability is commonly understood in terms of the fluctuation in the kinematic, kinetic, spatio-temporal, or physiological information. Here, we have focused on the estimation of knee joint angle (kinematic variable) synchronized with some of the kinetic and spatio-temporal gait parameters while an individual walked overground. Our system consisted of a pair of shoes with instrumented insoles and knee flexion/extension recorder unit having bend sensors. In addition, we have used the Coefficient of Variation for estimating the variability in the knee flexion/extension angle while walking overground as an indicator of the risk of fall. A study with healthy individuals (young and old) walking overground on pathways having 0^0 and 180^0 turning angles indicated the feasibility of our wearable system to compute the variability in knee flexion/extension angle as an indicator of the risk of fall.**

I. Introduction

Uninterrupted gait without falls is important [1] since it ensures mobility and healthy community life. One's lack of dynamic balance while walking can be a potential cause of falls [2] leading to lacerations, hip fracture, etc. One's risk of fall can be quantified in terms of variability in one's gait, reflecting a loss of automatic rhythm of one's gait [3]. In fact, the variability in gait arises from many potential sources, categorized as internal (e.g., aging effects) and external (e.g., nature of pathways) to the individual [4]. In gait analysis, variability is commonly understood in terms of the fluctuation in the value of a kinematic (e.g., joint angle), kinetic (e.g., ground reaction force), spatio-temporal (e.g., gait events), or physiological (e.g., lower limb electromyogram) information [4]. While electromyogram of one's lower limb muscles can quantify one's gait pattern, the data collection might be intrusive in nature [5]. In contrast, the spatio-temporal gait events, kinetic and kinematic parameters [4] can characterize one's gait in a non-intrusive manner. Here, we have focused on the estimation of joint angle (kinematic variable) of the knee joint (synchronized with some of the kinetic and spatio-temporal gait parameters) while an individual walks overground. The estimation of joint angle is a key component of analysis of human gait [6]. One's joint angles can be measured by using standard camera-based techniques, e.g., VICON [7] which though powerful, suffer from portability issues, high cost, line-of-sight issues, etc.

Given the importance of joint angle estimation and the need to have portable, wearable sensing to facilitate human gait analysis in free-living conditions, research had been focused on using Inertial Measurement Units (IMUs), Ultrasonic sensors, Goniometers, etc. However, the IMU-based systems suffer from drift problems, the Ultrasonic sensors entail considerable power consumption and Electro-Goniometers may not be suited for real-time measurement [6]. In this paper, we introduce a novel wearable system for estimation of knee flexion/extension angle during one's gait. Our system consisted of a pair of shoes with instrumented insoles and knee flexion/extension recorder unit having bend sensors (thereby overcoming the issues faced by the other sensing mechanisms). In addition, here we used Coefficient of Variation [4] for estimating the variability in one's gait in terms of variability in the knee flexion/extension angle while walking overground, as indicator to the risk of fall.

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II. System Design

Our system comprised of (A) Instrumented Shoes, (B) Knee flexion/Extension recorder, and (C) Waist Belt mounted Central Module.

A. Instrumented Shoes

A pair of shoes having Insoles impregnated with Force Sensitive Resistors (FSR *henceforth*) was used for recording gait events (e.g., heel-strike, toe-off, etc.). Here, we have used 0-445 N FSR (FlexiForce A201; from Tekscan) with an active diameter of 9.53 mm. The FSRs were placed at the toe, lateral and medial heel locations of each Insole (Fig. 1) to accommodate any possible foot inversion/eversion. The Insoles were calibrated with VICON (from Vicon Motion Systems Ltd.). For details, please see [8]. The analog signal (0-5V) from each FSR along with time stamping was acquired by a Central module (described below).

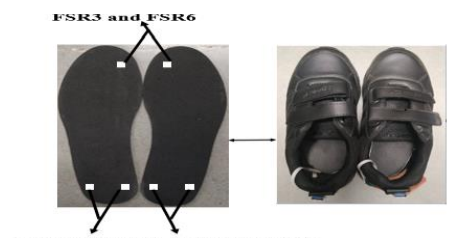


Fig. 1. Instrumented Shoes with Insoles.

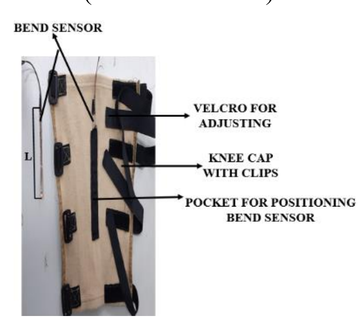


Fig. 2. Knee Flexion/Extension Recorder. Note: 'L'= 4.5inch.

B. *Knee Flexion/Extension Recorder Unit*

This unit had commercially available 4.5” bend sensor (from Spectra Symbol) positioned in the knee cap, adjustable with Velcro belts (Fig.2) for each leg. We calibrated the bend sensor (for details, please see Section III). The analog signal (0-5V) from the bend sensor along with time stamping was acquired by the Central module (described below).

C. *Waist Belt Mounted Central Module*

The Central Module (mounted on a Waist Belt) comprised of (i) Microcontroller (ATMEGA 2560), and (ii) Data Storage unit. This Module was used to acquire the time-stamped data from the Insoles (followed by 10-bit Analog-to-Digital conversion) and Knee flexion/Extension Recorder Unit. This data (along with shoe ID (namely, ‘left’ and ‘right’)) was routed to a 64 GB SD card (from SanDisk Ultra) Data Storage unit for subsequent offline analysis of knee joint flexion/extension corresponding to heel-strike and toe-off events (Figs. 3 (a) and (b)).

C.1 Extraction of Heel-strike Event

We wanted to understand one’s knee flexion/extension during the heel-strike with the base of support, since the initial loading with heel-strike is an important contributor to the bipedal stability [9]. The earliest valid peak (magnitude above a pre-selected threshold, chosen based on a pilot study) recorded by any of the FSRs placed at lateral and medial heel locations of left (L) and right (R) legs was used to extract the heel-strike information (‘L+’ and ‘R+’ (Fig. 3 (b)).

C.2 Extraction of toe-off Event

We also wanted to understand one’s knee flexion/extension during the toe-off event, important for maintaining balance [10] during gait, that in turn can determine the risk of fall. The toe-off event (‘L-’ and ‘R-’ for left and right legs, respectively (Fig. 3 (a))) was identified by finding the valley point of the toe FSR data (represented by ‘*’) immediately following the valid peak representing the heel-strike event (Fig. 3 (b)).

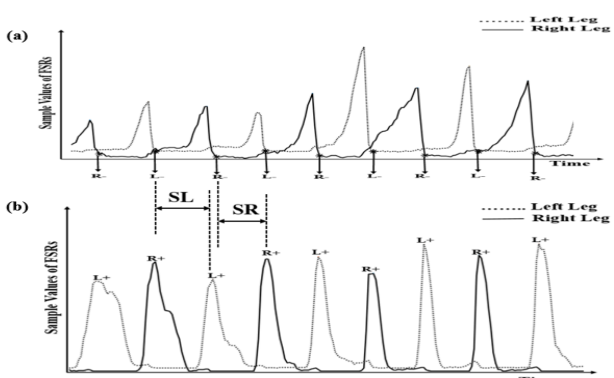


Fig. 3. Extraction of Gait Events, namely (a) Toe-off and (b) Heel-strike
Note:‘SL’ and ‘SR’ represent swing phase for left and right leg respectively.

C.3 Extraction of Swing Phase

We were interested to study how the knee flexion/extension angle varied during the swing phase. This is because, one’s gait pattern in the swing phase is an important indicator to postural balance and risk of falls [10]. Our system was used to record the swing phase of each leg (‘SL’ and ‘SR’ for left leg and right leg, respectively (Figs. 3 (a) and (b))) by computing the time interval between the ipsilateral toe-off and heel-strike events, during which the limb is not in contact with the base of support [11].

III. METHODS

A. Experimental Setup

Our study was conducted in Phase I (Calibration Phase of bend sensor (Section II.B)) and Phase II (Task Phase). The Phase I consisted of a stepper motor-hinge setup with motor driver, Arduino, a voltage divider (formed by 10KΩ fixed resistor and bend Sensor) and 5V regulated source. The setup comprised of a door hinge with one leaf of the hinge (moving arm; Fig. 4) connected to the shaft of a stepper motor and the other leaf being kept fixed (fixed arm). The Bend sensor was

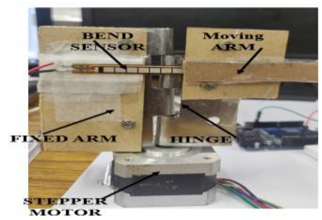


Fig. 4. Calibration Setup for Bend Sensor.

then pasted on the leaves of the hinge across the knuckles and care was taken that the bend sensor had 0^0 bend at the initial position. Also, the position of the sensor was adjusted to enable studying the sensor output with varying bend positions (Cases 1-3; Table I) with the pin out end (of bend sensor) being placed on the fixed arm. An Arduino-based code was used to achieve a step size of 1.8^0 of the stepper motor.

The Phase-II used (i) a pair of Instrumented shoes, (ii) pair of Knee Flexion/Extension Recorder units, (iii) 60 fps camera, and (iv) 10m overground pathway (with ‘START’ and ‘STOP’ lines) (Fig. 5 (a)). The pathway was of 2 types based on turn angle e.g., (a) $Path_0$ for 0^0 (i.e., Straight), and (b) $Path_{180}$ for 180^0 turning angle (Fig. 5 (b)).

TABLE I
BENDING POSITION DISCRIPTION

Case	Location of Bend
1	¼*L
2	½*L
3	¾*L

Note: ‘L’ represents length of bend sensor i.e., 4.5”.

B. Participants

Four healthy participants (Table II) were recruited from the neighborhood for taking part in Phase II of the study. Inclusion/exclusion criteria were (i) age between 18 and 90 years, (ii) able to walk independently for 10 m, (iii) can understand instructions from the experimenter, (iv) did not have any recent major surgery and (v) Falls Efficacy Scale (FES *henceforth*) [12]<70. Higher FES scores (for P3 and P4 than P1 and P2) indicate increased proneness to risk of fall.

TABLE II
PARTICIPANTS’ CHARACTERISTICS

ID	Gender	Age (Years)	FES Score
P1	M	25	10
P2	M	34	10
P3	M	64	28
P4	M	73	22

Note: FES Score- Falls Efficacy Scale Score [12]

The study had Institutional ethical clearance (Approval No.: IEC/2014-15/2/UL/003).

C. *Procedures*

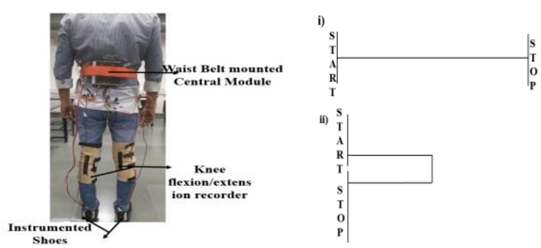
The procedures used during Phases I and II are discussed.

C.1 Procedure of Phase I

The Phase I was used to calibrate the bend sensor for varying bending angles (with the bending angle gradually increased in both clockwise (CW *henceforth*) and anticlockwise (ACW *henceforth*) directions about the bending location (Table I) with three trials for each Case. The range of bending angle was typically chosen as 0°to~100°.

C.2 Procedure of Phase II

The Task Phase (Phase II) required ~20 min from each participant. The study began with an introduction to the experimental setup. Also, the experimenter told that one was expected to walk overground on the $Path_0$ and $Path_{180}$ at his/her self-selected speed. Then the consent signing was administered. One was free to discontinue at any time if uncomfortable. Again, the fear of falling was assessed using the FES questionnaire [12]. The FES asks participants to rate their confidence on a 1-10 scale (higher scores indicate greater fear of falling) while performing ten daily living activities. Then the experimenter helped the participant to wear the Instrumented shoes, Knee Flexion/Extension Recorder Unit (with bend sensor on the kneepit), and the Waist Belt (Fig. 5 (a)). The participant was asked to stand



(a) (b)

Fig. 5. (a) Back view of a person during Phase II (b) 10m overground pathways with (i) $Path_0$ and (ii) $Path_{180}$.

with both legs touching the 'START' line (Fig. 5 (b)). A camera was used to record the video of one's walk for subsequent offline analysis. To synchronize the Central Module (on the Waist Belt) with the camera, one was asked to make three taps on the ground with any leg before starting to walk and then walk upto the 'STOP' line.

D. *Computation of Coefficient of Variation as Indicator to Risk of Fall*

Literature review shows that increased variability in one's gait can be indicative of higher risk of fall [3]. Such variability can be captured in terms of the Coefficient of Variation (CV). The CV is often used as a valuable measure for assessing the risk of falls in the elderly [3]. We computed the CV of the knee flexion/extension angle during heel-strike, toe-off and Swing Phase using Eq. (1).

$$CV = \frac{Standard\ Deviation}{Mean} * 100 \quad (1)$$

IV. RESULTS

While conducting our study in two Phases, namely Phase I and Phase II, we wanted to (i) calibrate the bend sensor (before using it to measure one's Knee Flexion/Extension angle) and (ii) understand the feasibility of our wearable system to quantify one's risk of fall. Also, we collected the participants' thoughts on the usage of our system.

A. User Feedback

After the participants completed the task of walking overground on the $Path_0$ and $Path_{180}$ (Section III) while using our system, the experimenter administered a post-study survey. A questionnaire was framed to know the participants' impressions while walking having worn (i) the waist belt, (ii) Instrumented shoes and (iii) the Knee Flexion/Extension Recorder unit. All of the participants told that the waist belt seemed light. None of them faced any inconvenience while walking with the shoes and the knee cap-based unit.

B. Calibration of the Bend Sensor

In this we were interested to understand (a) whether the bend sensor output (analog output) changed linearly with bending angles (applied using the stepper motor-hinge setup

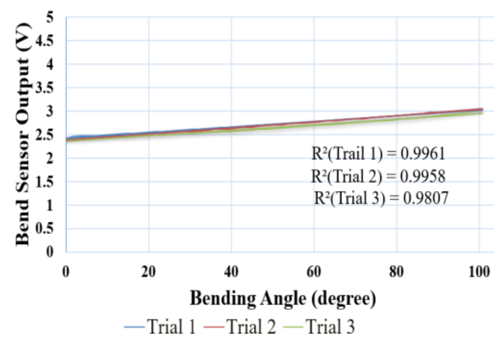


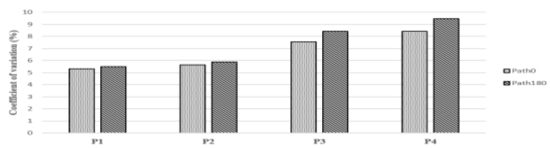
Fig. 6. Bend sensor output for different bending angles (for Case 2).

(Section III)) and (b) the repeatability of the bend sensor output when bent in CW and ACW directions (Section III). The bend sensor output changed linearly (R^2=~0.99) with the bending angle with Fig. 6 showing the output for Case 2. To understand the repeatability of the bend sensor output for ACW and CW, we computed the Pearson correlation coefficient [13] between the data points and found the coefficient to be >0.98 for each of the Cases 1-3.

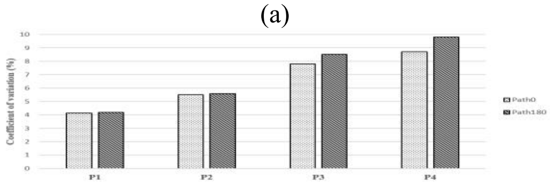
C. Variation of Knee Flexion/Extension Angle for each Participant as Indicator of Risk of Fall

Here we present the Coefficient of Variation (%CV) of the knee flexion / extension angle of each participant, P1 to P4 during heel-strike, toe-off and swing phase while they walked overground on $Path_0$ and $Path_{180}$. It can be seen from Fig. 7 that irrespective of the heel-strike, toe-off and swing phase of gait, the %CV of the knee flexion/extension angle increased with increase in participants' age, possibly inferring increasing proneness to fall with age, that is in line with literature [14]. In addition, increased pathway turn angle led to increased variation in the knee flexion/extension angle particularly for the elderly participants. In fact, these variations were found to be lower for P1 (%Change=%Δ=3.43, 0.77 and 0.47) and P2 (%Δ=3.83, 1.26

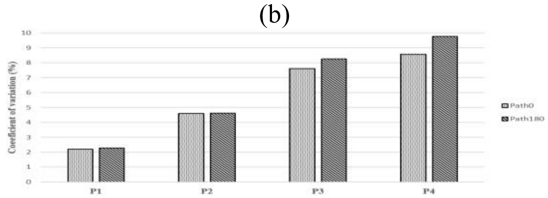
and 0.98) than that of P3 (%Δ=11.51, 9.07 and 8.46) and P4 (%Δ=12.5, 12.28 and 14.13), respectively during heel-strike, toe-off and swing phase. This variability may infer that the risk of fall increases with increase in the pathway turning



(a)



(b)



(c)

Fig. 7. CV of knee flexion/extension angle while walking on $Path_0$ and $Path_{180}$ during (a) Heel-strike (b) Toe-off (c) Swing phase.

angle, particularly in the elderly who are more prone to falls [15]. Our findings are also in line with the FES scores (Table II) with P3 and P4 showing lesser confidence than P1 and P2. Though the FES score of P4 (the eldest of the group) was lesser (by 6 units on a 1-100 scale) than P3, our results showed higher gait variability of P4 than that of P3 indicating P4 to be at a higher risk of falling than P3. Such discrepancy in the FES scoring may be possibly attributed to the subjectivity while responding to the FES questionnaire.

V. DISCUSSION AND CONCLUSION

Here, we presented the design of a wearable Knee Flexion/Extension Recorder system comprising of a bend sensor that can quantify one's knee flexion/extension angles and can be used as an indicator of one's risk of fall. We conducted a study in two phases, namely Phase I (Calibration Phase of bend sensor) and Phase II (Task Phase). The findings of Phase I showed that the bend sensor output changed linearly with bending angle and was repeatable. The results of Phase II indicated the feasibility of the Knee Flexion/Extension Recorder system to quantify one's risk of fall that increases with one's age and increase in pathway turning angle. Although, our findings were promising, yet our study had limitations. One of the limitations was the restricted sample size. In future, we plan to enroll a larger participant pool belonging to different age groups. Again, only a limited number of pathway turning angles (0^0 and 180^0) was used in our study. In future, we want to include pathways having a larger number of turning angles. Also, pathway contour (uphill and downhill) can be a contributor to falls. In future, we plan to incorporate various pathway contours in our study and quantify the risk of fall with our system. Notwithstanding the limitations, our study offers a stepping stone towards understanding the potential of a wearable technology to quantify one's risk of fall under varying walking conditions.

VI. ACKNOWLEDGEMENT

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REFERENCES

[1] V. F. Annese and D. De Venuto, "Gait analysis for fall prediction using EMG triggered movement related potentials," in *2015 10th International Conference on Design & Technology of Integrated Systems in Nanoscale Era (DTIS)*, Napoli, Italy, Apr. 2015, pp. 1–6, doi: 10.1109/DTIS.2015.7127386.

[2] M. Y. Osoba, A. K. Rao, S. K. Agrawal, and A. K. Lalwani, "Balance and gait in the elderly: A contemporary review: Balance and Gait in the Elderly," *Laryngoscope Investig. Otolaryngol.*, vol. 4, no. 1, pp. 143–153, Feb. 2019, doi: 10.1002/lio2.252.

[3] Y. Moon, D. A. Wajda, R. W. Motl, and J. J. Sosnoff, "Stride-Time Variability and Fall Risk in Persons with Multiple Sclerosis," *Mult. Scler. Int.*, vol. 2015, pp. 1–7, 2015, doi: 10.1155/2015/964790.

[4] T. Chau, S. Young, and S. Redekop, "Managing variability in the summary and comparison of gait data," *J. Neuroengineering Rehabil.*, vol. 2, p. 22, Jul. 2005, doi: 10.1186/1743-0003-2-22.

[5] M. Simao, N. Mendes, O. Gibaru, and P. Neto, "A Review on Electromyography Decoding and Pattern Recognition for Human-Machine Interaction," *IEEE Access*, vol. 7, pp. 39564–39582, 2019, doi: 10.1109/ACCESS.2019.2906584.

[6] S. I. Lee, J.-F. Daneault, L. Weydert, and P. Bonato, "A novel flexible wearable sensor for estimating joint-angles," in *2016 IEEE 13th International Conference on Wearable and Implantable Body Sensor Networks (BSN)*, San Francisco, CA, Jun. 2016, pp. 377–382, doi: 10.1109/BSN.2016.7516291.

[7] T. McGrath and L. Stirling, "Body-Worn IMU Human Skeletal Pose Estimation Using a Factor Graph-Based Optimization Framework," *Sensors*, vol. 20, no. 23, p. 6887, Dec. 2020, doi: 10.3390/s20236887.

[8] D. Solanki and U. Lahiri, "Design of Instrumented Shoes for Gait Characterization: A Usability Study With Healthy and Post-stroke Hemiplegic Individuals," *Front. Neurosci.*, vol. 12, p. 459, Jul. 2018, doi: 10.3389/fnins.2018.00459.

[9] J. Ros, J. M. Font-Llagunes, A. Plaza, and J. Kövecses, "Dynamic considerations of heel-strike impact in human gait," *Multibody Syst. Dyn.*, vol. 35, no. 3, pp. 215–232, Nov. 2015, doi: 10.1007/s11044-015-9460-0.

[10] E. Yiou, T. Caderby, A. Delafontaine, P. Fourcade, and J.-L. Honeine, "Balance control during gait initiation: State-of-the-art and research perspectives," *World J. Orthop.*, vol. 8, no. 11, pp. 815–828, Nov. 2017, doi: 10.5312/wjo.v8.i11.815.

[11] M. Arbulu, D. Kaynov, and C. Balaguer, "The Rh-1 Full-Size Humanoid Robot: Control System Design and Walking Pattern Generation," in *Climbing and Walking Robots*, B. Miripour, Ed. InTech, 2010.

[12] A. A. Thomas, J. M. Rogers, M. M. Amick, and J. H. Friedman, "Falls and the falls efficacy scale in Parkinson's disease," *J. Neurol.*, vol. 257, no. 7, pp. 1124–1128, Jul. 2010.

[13] W. Kirch, *Encyclopedia of public health: with 75 figures and 86 tables*. Dordrecht: Springer, 2008.

[14] P. E. Roos and J. B. Dingwell, "Influence of simulated neuromuscular noise on movement variability and fall risk in a 3D dynamic walking model," *J. Biomech.*, vol. 43, no. 15, pp. 2929–2935, Nov. 2010, doi: 10.1016/j.jbiomech.2010.07.008.

[15] A. B. Mane, T. Sanjana, P. R. Patil, and T. Sriniwas, "Prevalence and correlates of fear of falling among elderly population in urban area of Karnataka, India," *J. -Life Health*, vol. 5, no. 3, pp. 150–155, Jul. 2014, doi: 10.4103/0976-7800.141224.