Detecting and Differentiating Leg Bouncing Behaviour from Everyday Movements Using Tri-Axial Accelerometer Data

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ABSTRACT

Leg bouncing is assumed to be related to anxiety, engrossment, boredom, excitement, fatigue, impatience, and disinterest. Objective detection of this behaviour would enable researching its relation to different mental and emotional states. However, differentiating this behaviour from other movements is less studied. Also, it is less known which sensor placements are best for such detection. We collected recordings of everyday movements, including leg bouncing, from six leg bouncers using tri-axial accelerometers at three leg positions. Using a Random Forest Classifier and data collected at the ankle, we could obtain a 90% accuracy in the classification of the recorded everyday movements. Further, we obtained a 94% accuracy in classifying four types of leg bouncing. Based on the subjects' opinion on leg bouncing patterns and experience with wearables, we discuss future research opportunities in this domain.

KEYWORDS

accelerometer; behavioural markers; classification; fidget; leg bouncing; leg shaking; machine learning

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1 INTRODUCTION

Leg bouncing or leg shaking is a type of motor stereotypies that commonly occur in normal populations [6, 9]. It is even more prevalent in clinical populations with movement disorders such as restless legs syndrome and psychological disorders such as autism, schizophrenia, and attention-deficit/hyperactivity disorder [6, 17, 19]. These rhythmic, repetitive and often highly frequent movements are also considered as a form of foot fidgeting, among other crossing and uncrossing legs like behaviours. There are several patterns of leg bouncing such as heel or toe tapping, lower or upper leg swinging and jiggling, where many occur during sitting [2, 14]. It is often found to be associated with nervous and neurotic mannerism that reflects the level of tension or anxiety [10, 14, 17], but also with emotional states such as engrossment, boredom, excitement, fatigue, impatience, and disinterest [17, 18].

This purposeless and involuntary behaviour is often is an annoyance to the observers, as well as to people involved with it, hence viewed as unwanted behaviour. Further, body language experts recommend avoiding these behaviours as those can convey negative impressions to the observers [18]. However, recent research shows some benefits of small amounts of feet fidgeting as it prevents prolonged sitting-induced leg endothelial dysfunction and increases energy expenditure [3, 8]. Although there are some interventions designed aiming to promote its avoidance, it is not yet clear to what extend leg bouncing is harmful or helpful [20]. Further, some studies also provide insights on individual differences, based on visual observations; e.g. the quantity (duration and frequency) and quality (rhythm and smoothness) of leg jiggling are observed to be varying between two cultures [14]. However, it is not yet clearly understood what patterns and parameters of leg bouncing relate to various emotional and health states. Being able to objectively detect this behaviour with high accuracies despite the individual differences and the ability to detect continuously would enable reliably studying the related associations.

While many of the existing activity recognition datasets and analyses have not included leg bouncing [4, 5, 7, 11, 12, 21], there is a growing interest in objectively detecting this behaviour [1, 2, 20]. A previous study has detected jiggling using Microsoft Kinect [1], but this is not an option for ambulatory settings. One study has used accelerometry data of a smartphone in a user's pocket [20], but that is less feasible for continuous detection, as that approach conflicts with its primary way of use; i.e., holding in hands. Another study has classified different workspace activities, including leg shakes, using accelerometers at knees [13]. This study classified leg shaking at a 97.37% accuracy during sitting but have not included non-sitting activities in the classification. While none of these studies indicates which bouncing patterns were used, another study has included four types of leg bouncing patterns. This study detected leg-bouncing in general and four types of leg-bouncings during sitting at 95% and 91% accuracies, with an accelerometer attached to a shoe [2]. The current work points to that the use of accelerometers at leg allows continuous and accurate monitoring. However, it is not yet attempted to detect leg bouncing among other ambulatory activities such as walking, running, or cycling. Further, since existing studies have used different sensor placements, it is not yet clear which leg locations are suitable for higher accuracies.

We answer three research questions: (RQ1) can we accurately classify leg bouncing among other common movements using triple-axis accelerometer data (e.g., free sitting or standing, walking, stepping stairs, running, cycling, intentional rhythmic tapping)? (RQ2) can we accurately differentiate leg bouncing patterns such as heel-tapping, toe-tapping, upper leg swinging, lower leg swinging, and

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jiggling? (RQ3) which of the three leg-locations (knee, ankle, and dorsum) are suitable to detect and differentiate leg bouncing from other movements in terms of accuracy and users' preference to use in daily contexts? We answer these questions through a small-scale user study. Our research makes it another step closer to understand the underlying reasons behind leg bouncing in the future.

2 METHODS

2.1 Data Collection

Six healthy adults (aged: 27.5(±1.5); females: 50%) with leg shaking habits participated in this study. Six custom-made wearables were worn at knee, ankle, dorsum of each leg using four Velcro straps and two clippers to the shoes, always facing the same direction. See Figure 1 for the sensor placements. The wearables included NXP Semiconductors MMA8653FCR1 accelerometers that were capable of capturing up to ±2048 milli-g at a 100Hz sampling rate. The subjects followed the activities instructed by the researcher. A mobile phone application developed by the first author was used to start and finish accelerometer data recordings for each activity [15]. The data was captured through Bluetooth in real-time and saved to the phone storage.

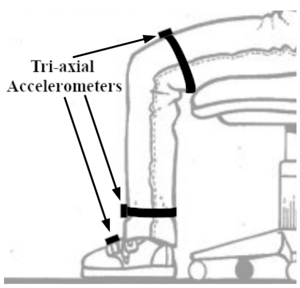

Figure 1: Sensor Placements

The series of activities used and their recording times were as in Table 1. This protocol resulted in a total of 150 seconds of leg bouncing, 120 seconds of low-movements, and 120 of non-leg bouncing high-movements for each subject. To obtain a more naturalistic dataset, we included varying types of low-movements (still sitting and standing, free sitting and standing with and without interactions, sitting down and standing up), high-movements (e.g., walking, running, cycling, feet tapping to music) and leg bounces. The types of leg bouncing included are: lower leg swinging (i.e., fast repetitive movement of the heel of one leg that is on the knee of the other leg), upper leg swinging (fast repetitive movement of both thighs in left and right directions while feet are constantly touching the ground), jiggling (i.e., fast repetitive swings of the lower leg in which thigh is crossed over the other thigh), and fast repetitive toe and heel tapping. Note that we have not included the uncommon "up and down leg bouncing" pattern used in [2]; instead. we included commonly observed heel and toe tappings. As a non-leg-bouncing movement, we included feet-tapping to music, as it has closer patterns to leg bouncing but with associations to relaxed and pleasant emotional states. We hypothesized that this movement would challenge the classification accuracies. We chose

Table 1: Activities and Recorded Duration (in order)

Activity	Duration (s)
Still-standing	10
Sitting down	5
Still-sitting	10
Heel tapping - right, left, both legs (sitting)	3x10
Upper leg swinging	10
Toe tapping - right, left, both legs (sitting)	3x10
Lower leg swinging - right, left	2x10
Jiggling - right, left	2x10
Free sitting while talking	20
Standing up	5
Free standing while talking	20
Toe tapping - right, left (standing)	2x10
Heel tapping - right, left (standing)	2x10
Sitting down	5
Free sitting without interactions	20
Free tapping to a slow and a fast music	2x20
Standing up	5
Walking	60
Climbing down, up stairs	2x20
Running	10
Free standing without interactions	20
Cycling	10

10-second duration for leg bounces as it is observed that leg bouncing occurs for a few seconds or less than a minute [14], and it is the same duration used in [2]. Other activity durations were chosen to balance the totals of three main activity categories.

The researcher demonstrated each leg bouncing pattern and then asked to perform it at their natural cadence. The recording was only initiated when they indicated that they are performing it as naturally as possible. After each pattern, they were asked how much they are familiar and used to those behaviours in a 3-scale Likert scale (not at all, somewhat, very much). The collected accelerometer dataset is available at [16].

On completion, the researcher asked three questions: (1) How uncomfortable was it to wear sensors at each leg position and if it was uncomfortable, at which instances did you feel so?, (2) What is your opinion on wearing similar sensors during extended periods and how do you think these sensors can be improved?, and (3) How often and in which situations do you think you do leg bouncing, and does it happen voluntarily?.

2.2 Analysis

The acceleration magnitude for each reading was calculated as $mag\_acc = \sqrt{x^2 + y^2 + z^2}$; where x, y, z are three acceleration components. We did not perform any preprocessing to filter out gravity effect or noise, as we aimed to obtain higher accuracies at low computational costs. After visualization of mag_acc graphs of each activity, we decided to segment data at 3-seconds intervals to feed the classifications, as that duration could capture the shapes of repetitive patterns and also it was small enough to detect short leg bouncing instances. Segmentation windows had no overlaps, for not to make it favourable for classification accuracies with repetitive data. All the subjects contributed to data points similarly without any data losses; however, one participant could not complete the cycling activity. For the leg bouncing patterns that involve only one leg (e.g., heel tapping with right leg), we did not include the reading from the other leg. We discarded the data points of patterns, where the subjects claimed to be unfamiliar. This resulted in a total of 4040 data points (leg bounces = 918, low-movements = 1275, walking = 709, stepping stairs = 426, running = 141, cycling = 139, music tapping = 432), considering two legs and data capturing leg positions separately. Within leg bounces, there were 216 heel taps, 207 toe taps, 99 upper leg swings, and 18 jigglings/ lower leg swings. Since jiggling and lower leg swinging were similar in patterns [2], we grouped those for the classification. Note that many subjects mentioned that this group of patterns were unfamiliar, lowering the number of data points.

We carried out four classifications with four features: four vectors of x-component, y-component, z-component, and mag_acc during each activity segment. First, we performed a binary classification involving only leg bouncing and low-movements (*2-level activities*). For the second classification, we included high-movements as a separate class (*3-level activities*). In the third classification, we split the high-movements into five classes: walking, stepping stairs, running, cycling, and music tapping, which altogether resulted in seven classes (*7-level activities*). In the fourth classification, we classified four types of leg bounces (*4-level bouncing*). We used ten machine learning classifiers with default parameters in Scikit-learn: Random Forest, Gradient Boosting, Logistic Regression, K-Neighbors, Decision Tree, Support Vector Machine, MLP, Gaussian Naive Bayes, AdaBoost and Gaussian Process classifiers. We used 80:20 training and test data splits and 10-fold cross-validation. Since we observed intra-individual differences in patterns along timeline even within the same activity, we chose 10-fold cross-validation over leave-one-out participant approach.

3 RESULTS

Out of the ten machine learning classifiers, Random Forest Classifiers (RFC) contributed to the best results across most of the four classification tasks, and then the Gradient Boosting Classifiers (GBC). Refer to Table 2 and Table 3 for the obtained accuracies for each sensor location. Readings collected at ankle position resulted in more accurate results. As the best results, leg bouncing and low-movements could be classified at a 98% accuracy; leg bouncing, low-movements and high-movements could be classified at a 92% accuracy; and seven activities including leg bouncing, low-movements, walking, stepping stairs, running, cycling, and music tapping could be classified at a 90% accuracy. Four types of leg bouncing could be classified at a 94% accuracy, by RFC at the ankle.

Figure 2 and Figure 3 provide the confusion matrix for seven activities and four types of leg bounces classified. According to Figure 2, leg bouncing could be differentiated from other activities at a 97% accuracy. Also, this behaviour is sometimes confused with low-movements and music tappings. According to Figure 3, jiggling and lower leg swinging are mostly confused with heel-tapping, and upper leg swinging is mostly confused with toe-tapping.

Table 2: Random Forest Classifier (RFC) based Results

Classification	Knee	Ankle	Dorsum
2-level activities	0.96 (±0.05)	**0.98 (±0.03)**	0.97 (±0.04)
3-level activities	0.90 (±0.05)	**0.92 (±0.05)**	0.91 (±0.05)
7-level activities	0.87 (±0.06)	**0.90 (±0.05)**	0.88 (±0.08)
4-level bouncing	0.90 (±0.14)	**0.94 (±0.09)**	**0.94 (±0.14)**

Table 3: Gradient Boosting Classifier based Results

Classification	Knee	Ankle	Dorsum
2-level activities	0.96 (±0.06)	**0.97 (±0.05)**	**0.97 (±0.04)**
3-level activities	0.90 (±0.04)	**0.91 (±0.03)**	0.90 (±0.04)
7-level activities	0.85 (±0.06)	**0.90 (±0.06)**	0.87 (±0.07)
4-level bouncing	0.92 (±0.15)	0.93 (±0.08)	**0.95 (±0.10)**

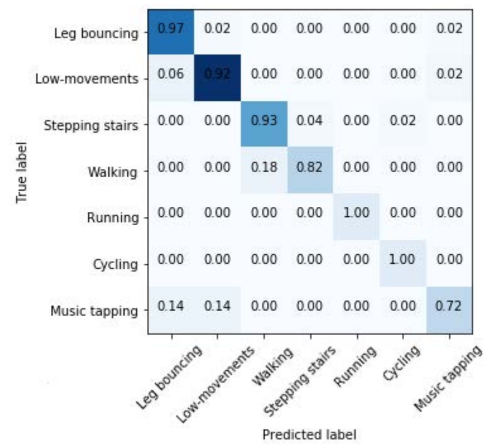

Figure 2: Confusion matrix for 7-level activities by RFC

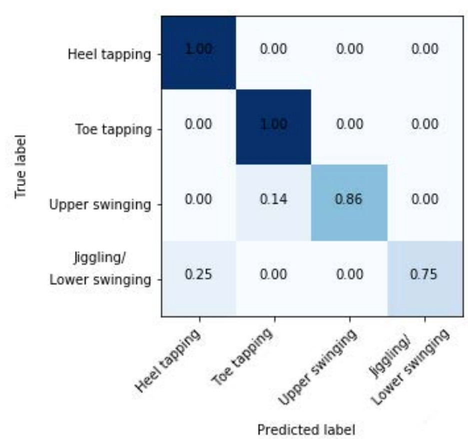

Figure 3: Confusion matrix for 3-level leg bouncing by RFC

As answers to follow up questions, all the subjects indicated that they barely noticed or felt the sensors worn at the ankle and dorsum, but they felt a slight tension caused by the strap at the knee, especially when bending the legs. As their opinions to wearing similar sensors in the daily context, 6/6 wanted the sensors to be less noticeable to the outsiders; hence, preferred wearing at the ankle covered by a trouser or socks. Also, many mentioned that they would not like to wear wearables directly contacting the body (e.g., knee guard, ankle band, skin patches). They wanted to wear on top of something, such that the presence of wearables is not going to distract them. Some suggested wearing as an unnoticeable shoe accessory (clipper to lace), wearing on top of socks, or attached to a shoe insole. The discussions also led to practical concerns, such as it is quite normal to forget wearing when changing shoes, it would be a burden to attach and detach even if those could be easily worn, it would disturb activities such as lace untying, there should be alternative ways to wear them depending on attire, and the wearable should be safe to wear. Among these concerns related to stigma, comfort and safety, a participant mentioned that unless there are health or other benefits (e.g., track activities or lace locking mechanisms), they would not wear in the long term. Another mentioned that the wearable could be fashionable.

Three participants mentioned that they bounce legs very often, and others were occasional leg bouncers. While four participants claimed that this behaviour happens involuntarily, others were not sure about how it happens. Participants thought that they bounce legs when thinking (3/6), feeling restless (2/6), and during specific activities like reading (1/6); however, they were not confident in these responses. Also, some mentioned that they want to stop unwanted leg bouncing, while others had no such concerns.

4 DISCUSSION AND CONCLUSION

The results indicate that we can detect and differentiate leg bouncing patterns from other everyday movements at high accuracies using limited tri-axial accelerator data-based features and Random Forest Classifier (RQ1). Tapping to music behaviour is a major reason for the resulted in false positives and false negatives. This points to the importance of including behaviorally similar but cognitively less similar patterns in exploratory data collections and working towards algorithmically differentiate such patterns. However, the confusions due to low-movements remain less explainable.

Some leg bouncing patterns were able to be differentiated from other bouncing patterns with high accuracies (RQ2). The reason for low accuracies in classifying jiggling and lower swinging can be due to the lower amount of data points in that class. This raise the need for collecting larger data samples in the future. However, this study has a higher ecological validity compared to existing studies that have used imitating leg bouncing patterns from general samples. This is because, in our study, we only included subjects who have leg bouncing habits and have discarded the patterns that they are not used to. However, in the future studies, it is vital to capture naturally occurring leg bounces, maybe through prompting for subjective inputs on automatically detected leg bouncing patterns. For such research, our results show promising directions.

Our findings show that ankle is the best sensor placement to detect and differentiate leg bouncing accurately, then the dorsum (RQ3). This placement was also favourable to our subjects compared to the knee. Although designing accelerometer-based wearables seems to be straightforward, our subjects' concerns about wearing such sensors in the long term point to the need for careful design, taking stigma, comfort, safety, practicality, and usefulness related concerns into account. Further, their less awareness about why leg bouncing is happening, beliefs of this behaviours' association to cognitions, and the individual differences in manipulations indicate its potential of being a behavioural marker for mental and emotional state detections, which and needs to be verified in future studies.

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