Inferring the Mood of a Community From Their Walking Speed: A Preliminary Study

Oludamilare Matthews
The University of Manchester
oludamilare.matthews@
manchester.ac.uk

Zhanna Sarsenbayeva
The University of Melbourne
zhanna.sarsenbayeva@
unimelb.edu.au

Weiwei Jiang
University of Tokyo
wjiang@akg.t.u-tokyo.ac.jp

Joshua Newn
The University of Melbourne
joshua.newn@unimelb.edu.au

Eduardo Velloso
The University of Melbourne
e.velloso@unimelb.edu.au

Sarah Clinch
The University of Manchester
sarah.clinch@manchester.ac.uk

Jorge Goncalves
The University of Melbourne
jorge.goncalves@unimelb.edu.au

UbiComp/ISWC'18 Adjunct,, October 8–12, 2018, Singapore, Singapore
ACM 978-1-4503-5966-5/18/10.
https://doi.org/10.1145/3267305.3274759

Abstract
The mood of a community influences work productivity, socioeconomic outcomes and general quality of life of its members, so being able to measure it opens a wealth of opportunities like, informing policies, scheduling events and possibly discovering the contexts that bring about undesirable moods within a community. Though there are a plethora of methods for measuring emotional states of individuals in lab settings (e.g. self-report, analysis of nonverbal behaviours, physiological sensors), they do not scale well to large numbers of people or *in-the-wild* settings. This paper examines the feasibility of inferring the mood of a community by measuring the walking speed of pedestrians, which is a technique that is unobtrusive, scalable, and readily available. Our preliminary results from our data collection reveal differences in walking speed at different times of the day; demonstrating the feasibility of our approach. We discuss the implications of our findings, followed by the future steps of this work.

Author Keywords
Walking speed; Community; Mood; Emotion; Affective computing; Body tracking; Microsoft Kinect

ACM Classification Keywords
H.5.m [Information interfaces and presentation (*e.g.*,, HCI)]: Miscellaneous.

Introduction

Mood is defined as the prevailing psychological state of an individual [3]. It is a prolonged feeling that influences the individual's cognition [4], motivation [10], productivity [5] and well-being [17]. Due to the impact of psychological states on these qualities of life indices, emotion and mood detection has been a popular subject of research in Psychology and Human-Computer Interaction [11, 12].

While lab-based approaches have been commonly used to capture the emotional state of individuals [22], mood detection in-the-wild is challenging [7] due to the lack of control of confounding variables, for example, participant demographic selection (gender, culture, age) and environmental conditions (weather, location, different periods). This paper explores the feasibility of using automatic sensing in-the-wild to assess the general mood of a community through the detection of their walking speed. Studies have identified relationships between specific characteristics of walking and psychological states. For example, Montepare et al. reported that observers can identify distinct emotions (pride, anger, happiness and sadness) from the gait style of people, and that happy people walk faster [13]. Moreover, Roether et al. showed that gait speed is a relevant feature for the perception of emotional activation (arousal) [16].

In this paper, we present the case for our approach by presenting the results of our preliminary study conducted over a period of five days. Our results show significant differences in walking speed during different times of the day, with the speed being the highest in the afternoon. We also found a trend of reduced speed by the hour, through the day. It is important to clarify that the scope of this approach is limited to people within a geographical location (neighbourhood, town or city). Understanding the general mood of a community and the contexts in which these moods are experienced could be of use to community leaders and event planners for increased well-being, and contribute towards quantified-self efforts [19]

Related Work

The literature suggests that understanding the emotions and feelings of others is an essential skill in everyday life [16]. Most of the research, studying human emotions and mood, centres on facial expressions [18]. In recent times, there has been a growing trend to derive mood from body postures [1]. Roether et al. showed a close link between characteristics of body movements such as speed, acceleration, to the emotional state of the individual [16]. More specifically, emotions such as anger and happiness are associated with faster than normal movements, whereas fear and sadness are associated with slower than normal movements [16]. With respect to walking behaviour, Montepare et al. suggests that walking speed varies substantially with emotions [13].

Previous work has also shown that human emotions and mood have diurnal rhythms [20, 9]. In a field study by Goncalves et al., passersby rated human silhouettes as sad-neutral-happy on public displays. The study results revealed diurnal rhythms of a community with peaks at noon and evenings for positive emotions, and peaks in mid-morning and mid-afternoon for negative emotions. This method has shown that the mood and emotional state of a community can be detected through projective testing on public displays. However, their approach requires the community to interact with the public display. Our proposed approach of using walking speed to determine addresses this limitation, as passersby do not need to interact with any technology, and hence, provides simplicity in assessing the mood of the community.

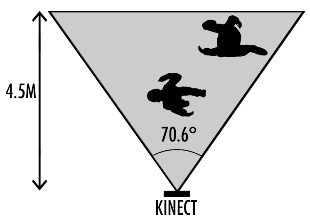

Figure 1: Top view of the Kinect's field of view (viewing angle is at 70.6 degrees and tracks up to 4.5 metres). We measure pedestrians as they enter from one side and exit on the other.

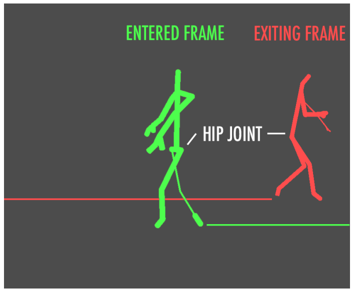

Figure 2: Screenshot of the Microsoft Kinect's skeletal tracking. We measure the position of the hip joint as the pedestrian enters and exits the frame.

The collective emotion and mood information gathered might help us to not only understand the given events that influence the mood of the community but also to monitor the duration and fluctuations of collective emotional state [6]. This knowledge can be used to provide timely help for communities in need to improve their quality of life and well-being.

Methodology

Procedure

To collect pedestrian velocity data, we built a recording setup using a Microsoft Kinect v2. Specifically, we recorded the positions of the joints as estimated by the Kinect SDK. This enabled us to record data anonymously, as there was no active recruitment of participants.

We deployed this setup along a wall in a corridor of the student union building at The University of Melbourne. The building was chosen due to its central location and that people often walk through the building throughout the day to their desired destinations on the university campus or within the building itself.

We sampled data over a period of five working days, in the morning between 9:30 am and 10:30 am, in the afternoon between 1:00 pm and 2:00 pm, and in the evening between 4:30 pm and 5:30 pm to observe periodic (morning, afternoon, evening) trends. On one of the days, data collection occurred between 9:30 am and 4:30 pm to observe hourly trends across the day. Being an academic environment, weekdays are the most active periods. Also, we assumed that resumption, lunch and closing periods would offer a variability in dwellers' moods. We captured the position and respective timestamps of pedestrians at a rate of 30Hz. We computed the walking speed from the total displacement per total time of each pedestrian as they walked through the visible field of view of the Kinect sensor.

Data Extraction

Over the duration of the study, we collected 4,984 data points. Because we do not collect identifiable information, it is likely that multiple data points could correspond to the same person. We defined two regions at the edges of the visible range of the sensor to allow for a margin of tolerance (see Figure 2). We then recorded the 3D coordinates of tracked skeleton's hip joint and timestamps of when the same pedestrian crossed these regions.

We discarded data corresponding to pedestrians who did not pass through both regions to ensure data completeness and to remove potential outliers. As a consequence, this approach also removed data from cases where the same person was tracked as a separate one in cases where the Kinect temporarily lost track of them due to occlusion. The total displacement was divided by the total time between their entry and exit point to compute the respective walking speed of each object. To achieve a 95% confidence interval, a bandpass filter is used to exclude anomalous speed values outside the percentile range [2.5%,97.5%]. After excluding incomplete data and outliers, a total number of 3,344 objects remained.

Results

Following the data extraction, records in the morning (*n=579*), afternoon (*n=1,292*) and evening (*n=553*) were analyzed. Table 1 shows the statistical description of the walking speed during these periods. Kruskal-Wallis test reveals that there is a significant difference in walking speed between these periods, $H(3) = 11.51$, $p=0.003$. From the data, people are more likely to walk faster in the afternoon than in the morning or evening, although, the data also reveals more variance in walking speed in the afternoon compared to the morning and evening period. Figure 3 shows a box plot of the walking speed in the morning, afternoon and evening.

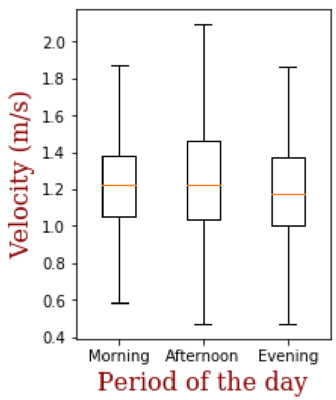

Figure 3: Box plot of the period of the day against the walking speed (m/s)

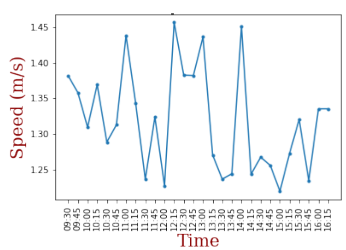

Figure 4: Graph showing the time of the day against the walking speed (m/s)

	Morning *0930-1030*	**Afternoon** *1300-1400*	**Evening** *1630-1730*
Count	579	1, 292	553
Mean (m/s)	1.28	1.36	1.26
SD	0.44	0.58	0.48
Min (m/s)	0.40	0.45	0.43
Max (m/s)	4.58	4.60	4.87

Table 1: Statistical description of the walking speed in the morning, afternoon and evening period.

On the final day of data collection (a Friday), we collected data from 9:30 am to 4:30 pm, which made it possible to perform analysis on the data per hour. For this, we analysed the 1,228 records that met the inclusion criteria described in the Data Extraction section. The walking speed during this period ranged from 0.43 m/s to 4.98 m/s with a mean walking speed of 1.32 m/s (SD = 0.56).

Figure 4 illustrates the walking speed trend throughout the day. There is a negative correlation r(8)=-0.79, p=0.021 between the average speed each hour, and the hour of the day. As with results from Figure 3, we can see spikes in walking speed in the early afternoon, with slower walking speeds registered in the morning and evening.

We also tested if there was a relationship between people's walking speed and their height; however, our analysis showed no correlation between the two variables r(3, 208)=-0.01, p=0.6. Furthermore, our analysis did not reveal any significant correlation between the walking speed and the number of people walking per hour (r(8)=-0.29, p=0.493).

Discussion

Measuring community's mood is a challenging endeavour because of the several contextual factors that need to be considered. As such, the lack of contextual factors in this study (*e.g., community activities, events, weather, and location*) could limit the generalizability of its findings. However, the primary goal of this study was to examine the feasibility of using the average walking speed of people in a community as a proxy for sensing the mood of the community.

Our findings corroborate evidence found in the literature. For example, Goncalves et al. has previously shown that the mood and emotions of a community can fluctuate during the day [9]. From our results, we observed a similar trend in walking speed throughout the day [9]. Trends from our study and the study by Goncalves et al. show higher positive emotions after lunch, and lower positive emotions in the mornings and in the evenings. This finding works as evidence that the emotional state of the community corresponds to its walking speed.

Furthermore, Wilson et al., in a study about personality, time of the day and arousal, observed an increase in Electrodermal Activity (EDA) at noontime compared to other periods of the day [21]. The EDA (a physiological correlate of arousal [15]) measures in the study by Wilson et al. provide additional evidence of the correlation between arousal and walking speed observed in this study.

Limitations

It is estimated that up to 70% of people moving in a crowd walk in groups of friends, family couples. The social interaction between them plays a role in their walking speed as opposed to individuals commuting with less social involvements [14]. In an investigation about crowd density and the corresponding moving speed of pedestrians, a logarithmic correlation between both variables showed that people walk slower when it is crowded [8]. This study does not validate this hypothesis as there was no significant correlation (r(8)=-0.29, p=0.493) between the walking speed and the number of people per hour. Possibly, this effect was not observed in our study because there was no congestion to the point of disrupting free-flowing movement along the corridor. Furthermore, the relationship between people's height and their gait characteristics (speed, stride length, etc.) has often been reported in the literature [2]. This was not validated in our study, as there was no correlation between the two variables.

Future Work

This preliminary study aims to investigate the possibility of using the average walking speed of individuals in a community to sense the general mood of the community. Our preliminary results are promising and worthy of further exploration. A follow-up study will be deployed at multiple locations on the University's campus for one year. During this period, information about the emotional state of people will be collected using a variation of self-reports. This counterpart data collection will be deployed around the same location as each Kinect sensor device. Sentiment analysis will be performed on the local community's tweets and will act as a ground truth about the general mood of the community, along with the self-reported emotions. Furthermore, the community's mood will be correlated with different contextual factors (*e.g., local or global events, and weather*) to find out if there exists a relationship between these variables.

Conclusion

In this study, we used walking speed of individuals as a gauge to infer community's mood. We identified a trend of significant decrease in walking speed from morning to evening, but higher average speed in the afternoon compared to morning and evening periods. We also showed that the walking speed of the community varies significantly at different hours of the day. Our findings are consistent with findings from prior research and demonstrated that the community's average walking speed can be used to determine its mood.

Acknowledgement

This work was supported by JST ERATO Grant Number JP-MJER1501 and the University of Melbourne-University of Manchester Research Fund.

REFERENCES

1. Atkinson, A. P., Tunstall, M. L., and Dittrich, W. H. Evidence for distinct contributions of form and motion information to the recognition of emotions from body gestures. *Cognition 104*, 1 (2007), 59–72.
2. Charalambous, C. P. Walking patterns of normal men. In *Classic Papers in Orthopaedics*. Springer, 2014, 393–395.
3. Clark, A. V. *Psychology of moods*. Nova Publishers, 2005.
4. Clark, D. M., and Teasdale, J. D. Constraints on the effects of mood on memory. *Journal of Personality and Social Psychology 48*, 6 (1985), 1595.
5. Coutts, R., Gilleard, W., and Baglin, R. Evidence for the impact of assessment on mood and motivation in first-year students. *Studies in Higher education 36*, 3 (2011), 291–300.
6. De Gelder, B. Towards the neurobiology of emotional body language. *Nature Reviews Neuroscience 7*, 3 (2006), 242.
7. Dhall, A., Goecke, R., Ghosh, S., Joshi, J., Hoey, J., and Gedeon, T. From individual to group-level emotion recognition: Emotiw 5.0. In *Proceedings of the 19th*

ACM International Conference on Multimodal Interaction, ACM (2017), 524–528.

8. Fang, Z., Lo, S., and Lu, J. On the relationship between crowd density and movement velocity. *Fire Safety Journal 38*, 3 (2003), 271–283.
9. Goncalves, J., Pandab, P., Ferreira, D., Ghahramani, M., Zhao, G., and Kostakos, V. Projective testing of diurnal collective emotion. In *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, ACM (2014), 487–497.
10. Houser-Marko, L., and Sheldon, K. M. Eyes on the prize or nose to the grindstone? the effects of level of goal evaluation on mood and motivation. *Personality and Social Psychology Bulletin 34*, 11 (2008), 1556–1569.
11. Liu, Y., Goncalves, J., Ferreira, D., Hosio, S., and Kostakos, V. Identity crisis of ubicomp?: Mapping 15 years of the field's development and paradigm change. In *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, UbiComp '14, ACM (New York, NY, USA, 2014), 75–86.
12. Liu, Y., Goncalves, J., Ferreira, D., Xiao, B., Hosio, S., and Kostakos, V. Chi 1994-2013: Mapping two decades of intellectual progress through co-word analysis. In *Proceedings of the 32Nd Annual ACM Conference on Human Factors in Computing Systems*, CHI '14, ACM (New York, NY, USA, 2014), 3553–3562.
13. Montepare, J. M., Goldstein, S. B., and Clausen, A. The identification of emotions from gait information. *Journal of Nonverbal Behavior 11*, 1 (1987), 33–42.
14. Moussaïd, M., Perozo, N., Garnier, S., Helbing, D., and Theraulaz, G. The walking behaviour of pedestrian social groups and its impact on crowd dynamics. *PloS one 5*, 4 (2010), e10047.
15. Picard, R. W., Fedor, S., and Ayzenberg, Y. Multiple arousal theory and daily-life electrodermal activity asymmetry. *Emotion Review 8*, 1 (2016), 62–75.
16. Roether, C. L., Omlor, L., Christensen, A., and Giese, M. A. Critical features for the perception of emotion from gait. *Journal of vision 9*, 6 (2009), 15–15.
17. Salovey, P., and Birnbaum, D. Influence of mood on health-relevant cognitions. *Journal of Personality and social Psychology 57*, 3 (1989), 539.
18. Sarsenbayeva, Z., Ferreira, D., van Berkel, N., Luo, C., Vaisanen, M., Kostakos, V., and Goncalves, J. Vision-based happiness inference: a feasibility case-study. In *Proceedings of the 2017 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, ACM (2017), 494–499.
19. van Berkel, N., Luo, C., Ferreira, D., Goncalves, J., and Kostakos, V. The curse of quantified-self: An endless quest for answers. In *Adj. Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, UbiComp Adj., ACM (2015), 973–978.
20. Visuri, A., Sarsenbayeva, Z., Goncalves, J., Karapanos, E., and Jones, S. Impact of mood changes on application selection. In *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct*, ACM (2016), 535–540.
21. Wilson, G. D. Personality, time of day and arousal. *Personality and individual differences 11*, 2 (1990), 153–168.
22. Zeng, Z., Pantic, M., Roisman, G. I., and Huang, T. S. A survey of affect recognition methods: Audio, visual, and spontaneous expressions. *IEEE transactions on pattern analysis and machine intelligence 31*, 1 (2009), 39–58.