Posture Noise and the Measured Probability to Fall

Radostina K. Koleva
Electrical and Computer Engineering Department,
University of Maryland, College Park MD 20742

A. Widom and D. Garelick
Physics Department, Northeastern University, Boston MA 02115

Meridith Harris, Bryan A. Spinelli, Amanda E. Finn, Kellie Bonner,
S. White, Vijay Daryanana, P. Nyatsambo, M. Patel, and R. Sampson
Department of Physical Therapy, Northeastern University, Boston MA 02115
(Dated: November 18, 2018)

Experimental evidence is presented connecting small fluctuations in the posture of a quiet standing subject and the probability that the subject will have an accidental fall within a time period of one year. The data can be understood on the basis of random velocity fluctuations providing kinetic energy in dynamical posture modes. The kinetic energy can activate a transition over a potential energy barrier which keeps subjects in a metastable standing mode. The probability for a fall then follows an Arrhenius activation law.

PACS numbers: 87.45.D, 05.40, 87.53.T

I. INTRODUCTION

In recent years there has been considerable interest in the nature of posture sway [1, 2, 3, 4, 5, 6, 7]. Sway is the name given to the small dynamic displacement fluctuations present in the posture coordinates of a person who is otherwise standing quietly. Some studies have been motivated (in part) by a practical medical problem, i.e. the consequences of falling for the elderly population [8, 9, 10]. Such falls are frequent events. Medical studies show that ~ 40% of the elderly population experience a fall at least once a year causing fractures, contusions, head injuries, joint distortions and dislocations [11, 12]. The medical costs in the United States are ~ $10^{17}$/year [13, 14]. These figures suggest the desirability of a reliable screening technique for determining balance impairment, especially among the elderly. Our purpose is to present experimental evidence concerning the connection between noise processes in posture sway and the probability of falling. Some theoretical notions concerning this connection have been previously discussed [14].

In Sec.II, the experimental methods employed in measuring posture sway coordinates are discussed. The central instrument involved in the measurement is a sound wave assessment device (SWA). In Sec.III, the free energy barrier model [14] for computing the probability of a fall is discussed. The most important posture parameter determining the probability of a fall is the root-mean-square (rms) velocity $v$ of the fluctuating anteroposterior (back and forth) posture oscillation mode. The probability for a fall is to be described by the function

$$p(v) = e^{-u/v^2}, \quad (1)$$

where $u^2$ is proportional to the height of an energy barrier preventing a fall. Eq.(1) will be simply derived in what follows, but here one may note that $u$ gives rise to a single parameter fit to the data on posture sway and the probability of a fall. A maximum likelihood analysis of $u$ from experimental data is discussed in Sec.IV. In the concluding Sec.V, we discuss the utility of the energy barrier view in predicting the fallers within the elderly population.

II. EXPERIMENTAL PROCEDURE

The SWA device consists of two small ultrasonic transducers of the type used by Polaroid for auto-focusing cameras. Each transducer is able to emit and detect ultrasonic pulses at 30 Hz. When positioned some distance apart, say $L \approx 170$ cm, the transducers are able to determine the distance between them by measuring the time it takes for a pulse to propagate from one transducer to the other. The position accuracy of such a measurement is $\Delta x \approx 0.02$ cm.

The above technique is well suited for the measurement of the fine movements of subjects during quiet standing. One transducer is attached to the lower back (around the waist line) of a subject. The other transducer is positioned on a stable laboratory stand. The duration of the quiet standing measurement is 60 seconds.

The subjects participating in this study were 56 mature adults of ages from 60 years to 97 years residing in independent community residential facilities. The subjects filled out a questionnaire in order to determine their medical history and their history of falls. The subjects included in the study all had good ability to follow directions, good visual activity, good hearing and the ability to stand without assistance for at least 60 seconds. Excluded were subjects who had unstable cardiac diseases, orthostatic hypertension, severe neurological dis-
eases, blindness, diabetes, mental diseases, or lower extremities amputations.

The subjects were asked to stand for one minute while their movement (back and forth) in the anteroposterior direction was measured - i.e. the posture coordinate displacement $x(t)$ was recorded. The time interval $\Delta t$ between displacement measurements was $\Delta t^{-1} = 30$ Hz. The rms velocity $v = \sqrt{<\vec{x}^2>}$ was determined from the measured displacements and time intervals between displacement measurements.

The measured rms velocity $v$ was recorded within a bin of size $\Delta v = 0.05$ cm/sec. In the $k^{th}$ data bin of rms velocity $|v - v_k| < (\Delta v/2)$, $N_k$ subjects were studied. Of these, $n_k \leq N_k$ subjects indicated that they had a fall within the last year. The measured probability for falling within a year was taken to be the fraction $p_k = (n_k/N_k)$.

III. THEORETICAL MODEL

The physical kinetics of thermally activated processes is often modeled using a free energy of activation $\phi$ and a temperature $T$. The Arrhenius law for the probability $p$ of overcoming a local activation barrier and falling from a meta-stable free energy to a lower stable free energy is given by

$$p = e^{-\phi/k_B T}.$$  \hspace{1cm} (2)

The temperature in the Arrhenius law represents the thermal rms velocity $v$ of the coordinate describing the free energy barrier; i.e. for a coordinate associated with a mass $\mu$, the equipartition theorem of statistical mechanics asserts that

$$\mu v^2 = k_B T. \hspace{1cm} (3)$$

Expressing the energy barrier in terms of a “velocity” $u$ via

$$\mu u^2 = \phi \hspace{1cm} (4)$$

yields

$$p = e^{-u^2/v^2}. \hspace{1cm} (5)$$

Our model Eq.(1) is merely Eqs.(2) and (5) in thinly disguised form. However, the following physical points are worthy of note: (i) The “noise temperature” $T_n$ (with $\mu v^2 = k_B T_n$) of living beings is not the environmental temperature $T$. An object in thermal equilibrium with its environment is dead! The measured rms velocity $v$ of the living subjects represents noise but not thermal noise. (ii) The velocity $u$ (assumed independent of noise temperature) is still determined by the energy barrier which prevents us from falling without (say) being pushed.

The potential energy and energy barriers, at various measured posture coordinate x values, describes a combination of motions of the ankles and hips [16, 17, 18, 19]. The motions (referred to as “strategies” in the biomedical literature) are familiar to many casual observers. A loss of balance may often be preceded by large amplitude rocking back and forth (without stepping protections) before the final fall actually takes place.

The theoretical probability for a fall as a function of rms velocity is shown in FIG. 1. Note that the probability for a fall becomes appreciable when the rms velocity $v$ is somewhat greater than half the value of $u$. The experimental determination of $u$ is thereby of great interest.

IV. DATA ANALYSIS

For $\{N_k\}$ subjects having an rms velocities $\{v_k\}$, the total probability of having $\{n_k < N_k\}$ falling subjects is theoretically given by the binomial distribution

$$W = \prod_k \left\{ C(N_k, n_k) p(v_k)^{n_k} (1 - p(v_k))^{(N_k - n_k)} \right\}, \hspace{1cm} (6)$$

where

$$C(N_k, n_k) = \frac{N_k!}{n_k!(N_k - n_k)!}. \hspace{1cm} (7)$$

The likelihood of a particular value of the parameter $u$ is obtained from the probability distribution $W$ in Eq.(6) by inserting the experimental data $\{n_k^{(data)}, N_k^{(data)}\}$ into

$$L(u) = KW \left[ \left( n_k^{(data)}, N_k^{(data)}; u \right) \right], \hspace{1cm} (8)$$

where $K$ is an arbitrary constant.
The likelihood function $L(u)$ for the data at hand is plotted in FIG. 2. The likelihood $L(u)$ has a well defined peak at $u_{(\text{best fit})} = 0.40 \text{ cm/sec}$ which (in this analysis) is the best value of $u$ for fitting the experimental data. The likelihood peak gives rise to a clear picture of the uncertainty in the value of $u$. If one draws a horizontal line on the likelihood plot with $c\%$ of the area under the likelihood peak being above the horizontal line, then one obtains upper and lower bounds to $u$ by the two intersections of the line with the likelihood peak. The upper and lower bounds are thereby estimated with a confidence level of $c\%$.

Shown in FIG. 3 are three plots of the probability for a fall, together with the experimental points

$$p_k^{\text{experiment}} = \left( \frac{u_k^{(\text{data})}}{N_k^{(\text{data})}} \right).$$

(9)

The solid curve is the fit of the theoretical “probability of a fall” curve in FIG. 1 with the experimental data points employing the value of $u$ determined by the maximum likelihood in FIG 2. The upper and lower bounds are shown by dashed curves also obtained from the likelihood curve at a confidence level of 95%. Given the number of tested subjects, the agreement between theory and experiment is satisfactory. Higher numbers of subjects would be expected to improve the analysis by somewhat narrowing the likelihood peak.

V. CONCLUSION

Experimental evidence has been presented relating the rms velocity $v$ of the anteroposterior posture oscillation mode to the probability of a fall. In terms of the noise temperature of this posture mode

$$k_B T_n = \mu v^2,$$

(10)

the data can be reasonably understood on the basis of random velocity fluctuations providing kinetic energy. The kinetic energy can then activate a transition over that potential energy barrier which normally keeps subjects in a metastable standing mode. The probability for a fall then follows an activation law

While the single parameter $u$ gives a reasonable picture of the probability of a fall as shown in FIG. 3, several other parameters have been examined but play a minor role in determining the probability for a fall. These other factors include the expressed fear of falling, self perception of balancing ability, the mass body index and muscle strength.

The existence of an energy barrier to a fall is susceptible to further experiments. If one leans forward or backward beyond a certain critical displacement, then balance is lost unless one employs the step strategy. By measuring the potential energy change required to reach this critical displacement, the quantity $u$ can be estimated.

Finally, this project was started in order to design an instrument which could identify fallers within an elderly community. It appears that the SWA device is useful in achieving this goal.

FIG. 2: Shown is the experimental likelihood $L(u)$ of finding a barrier to a fall described by the parameter $u$.

FIG. 3: Shown as a solid curve is the best theoretical fit to the probability data points found from the maximum likelihood. The theoretical probability for a fall is in reasonable agreement with the experimental results. The dashed curves represent both the upper and lower bounds to the probability for a fall at a 95% confidence level.
Acknowledgments

The authors would like to thank Carlos Tun for his contributions to the early stages of this project.

[1] F. Alonso-Sánchez and D. Hochberg, Phys. Rev. E 62, 7008 (2000).
[2] C. C. Chow and J. J. Collins, Phys. Rev. E 52, 907 (1995).
[3] J. J. Collins and C. J. DeLuca, Phys. Rev. Lett. 73, 764 (1994).
[4] J. J. Collins and C. J. DeLuca, CHAOS 5, 57 (1995).
[5] M. Lauk, C. C. Chow, A. E. Pavlik and J. J. Collins, Phys. Rev. Lett. 80, 413 (1998).
[6] S. Thurner, C. Mittermaier, R. Hanel and K. Ehrenberger, Phys. Rev. E 62, 4018 (2000).
[7] W. Yao, P. Yu and C. Essex, Phys. Rev. E 63, 021902 (2001).
[8] J. J. Collins, C. J. DeLuca, A. Burrows, and L. A. Lipsitz, Exp. Brain Res. 104, 480 (1995).
[9] G. I. Firsov, M. G. Rosenblum and P. S. Landa, “AIP Conference Proceedings 285: Noise in Physical Systems and 1/f Fluctuations” page 717 AIP Press, New York (1993).
[10] M. Rosenblum, G. Firsov, P. Kuiz and B. Pompe, in “Nonlinear Analysis of Physiological Data” Kantz H, Kurths J, Mayer-Kress G Editors, Springer Verlag Berlin (1998).
[11] E. Gregg, M. Pereira, and C. Caspersen, Journal of American Geriatric Society 48, 883 (2000).
[12] P. Kannus, S. Niemi, M. Palvanen, and J. Parkkari, Archives of Internal Medicine 160, 2145 (2000).
[13] C. Sherrington and S. Lord, Gerontology 44, 340 (1998).
[14] R. K. Koleva, A. Widom, D. Garelick and M. Harris, Physica A 293, 605 (2001).
[15] R. Kubo, “Statistical Mechanics”, page 13, North-Holland, Amsterdam (1999).
[16] L. M. Nashner and G. McCollum, Behav. Brain Sci. 8, 135 (1985).
[17] A. Schumway-Cook and M. Wallacot, “Motor Control: Theory and Practical Applications”, page 119, Williams & Wilkins, Baltimore (1995).
[18] M. Whittle, “Gait Analysis: An Introduction” Butterworth & Heinemann, London (1991).
[19] D. A. Winter, “Biomechanics and motor control of human movement” John Wiley & Sons, New York (1990).