Statistical Modeling of Harvestable Kinetic Energy for Wearable Medical Sensors

Nathalie Yarkony, Kamran Sayrafian-Pour, Antonio Possolo
Information Technology Laboratory
National Institute of Standards and Technology
Emails: {yarkony, ksayrafian, Antonio.possolo}@nist.gov

Abstract—**Energy Harvesting (EH) refers to the process of capturing and storing energy from external sources or ambient environment. Kinetic energy harvested from the human body motion seems to be one of the most convenient and attractive solution for wearable wireless sensors in healthcare applications. Due to their small size, such sensors have a very limited battery power supply, which necessitates frequent recharge or even sensor replacement. Energy harvesting can prolong the battery lifetime of these sensors. This could directly impact their everyday use and significantly help their commercial applications such as remote monitoring. In this paper, our aim is to estimate the amount of harvestable energy from typical human motion. To simplify the measurement process, we focus on the amount of kinetic energy harvested from the human forearm motion. We provide statistical analysis of measurements taken from 40 test subjects over a period of 8 hours during the day. Using this information and knowing the operational architecture of the harvesting device, the distribution of harvestable energy can also be determined. Our objective is to study whether kinetic energy generated by typical human forearm motion could be a promising supplemental energy resource that prolongs the operational lifetime of wearable medical sensors.**

Keywords- Energy Harvesting; Wearable wireless sensors; Uncertainty analysis; Triaxial accelerometer

I. INTRODUCTION

Wearable and implantable wireless sensors have become a promising interdisciplinary research area in pervasive health information technology. However, there are still numerous challenging issues including reliability, cost, sensing/actuator technology, privacy/security and power efficiency. RF-enabled wearable sensors offer an attractive set of e-health applications among which we can point to various medical & physiological monitoring such as temperature, respiration, heart rate, and blood pressure. As these sensors mainly rely on very small batteries to carry their functions, prolonging their operational lifetime could significantly help their commercial applications.

Energy Harvesting (EH) refers to the process of capturing and storing energy from external sources or ambient environment. There are few sources from which we can harvest energy for wearable medical sensors, amongst them we can point to body heat and typical movement of human body. For example, a thermopile device can be attached to the body to convert its thermal energy into electrical energy [1,2]. This is called Thermoelectric EH. On the other hand, random motion of our arms and legs could generate kinetic energy that piezoelectric materials can convert to electrical energy [3,4]. Kinetic energy harvested from the human body motion seems to be one of the most convenient and attractive solutions for wearable wireless sensors in healthcare applications. Due to their small size, such sensors have a very limited battery power supply which necessitates frequent recharge or even sensor replacement. Energy harvesting can prolong the battery lifetime of these sensors. This could directly impact their everyday use and significantly help their commercial applications such as remote monitoring of physiological signs (i.e. telemedicine).

The kinetic energy harvesting systems operate similarly to a typical spring and damper system as shown in Fig. 1. Here, x represents the mass displacement, k is the spring constant and F is the force acting on the mass. The direction of the force that acts on the mass distinguishes two categories of kinetic-based EH namely the direct versus the inertial force. In the first method, (i.e. direct force) the direction of the force F opposes the motion; while in the inertial method (i.e. acceleration) F is applied along with the motion. The most common examples of direct force EH are the heel strike, shoe sole (bending the ball of the foot), and knee joints (i.e. movement of adjacent body parts) [3,5-6]. A good example for inertial EH that is already in widespread use is the kinetic watch [1]. An advantage of inertial EH devices is that architecturally they employ one attachment point to the moving structure; therefore, their physical size can be minimized more efficiently compared to direct force energy harvesters [3]. This makes them an appropriate candidate for wearable body sensors that are desired to be very small in size.

Current research on energy harvesting mostly revolves around the device technology. However, another fundamental question that needs to be addressed is the applicability of EH for wearable sensors in terms of the amount of producible energy. In this paper our objective is to investigate this question by statistical modeling of acceleration generated as a result of typical human body motion during the course of a day; and then estimating the average power that can be generated by an EH device. For simplicity, here we only focus on the human forearm motion. In the future, we plan to extend our studies to other parts of the body as well.

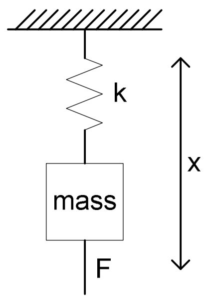

Figure 1. Spring and Damper system

The remainder of this paper is organized as follows. Section II describes the measurement process and statistical modeling of acceleration. Distribution of the generated average power by an inertial-based EH device is presented in section III. Finally, conclusions and our plans for future work are discussed in Section IV.

II. Measurement Process and Statistical Modeling of Typical Acceleration

To measure the amount of forearm acceleration, we have used the X6-1 [1] USB triaxial accelerometer. The accelerometer is attached to the forearm as shown in Fig. 2, The measurement samples are time-stamped and stored in the on-board memory so that they can be retrieved at a later time. The amplitude and frequency of human body accelerations during normal daily activities can range from -12 to 12 g and up to 20 Hz respectively [7]. However, there are rare occurrences of higher frequencies, for example at the foot and during heel strike when we walk. In this study, we chose a sampling rate of 32 Hz for acceleration measurements with an amplitude range of ±12g. The accelerometer was worn for up to 8 hours during the day by 40 different individuals [2] and a total of 320 hours of measurement data were obtained.

The test subjects range in age between 20 to 55 years, almost the same number of male and female, and various body types. Figure 3 displays a sample acceleration data (on the z axis) obtained through 8 hours of measurements. As observed, the absolute value of the acceleration amplitude for this sample ranges from -3 to +3 g.

The amplitude of the measured acceleration in general depends on the individuals involved in the measurement process. We recognize the fact that the forearm acceleration could depend on many factors such as individuals age, gender, profession, handedness and type of activities they are involved as part of their daily life. But for simplicity, here we will not define separate profiles of acceleration based on these factors. During processing of the data, we realized that the output of the triaxial accelerometer exhibits some constant bias on each axis. Therefore, before further analysis, we had to remove the bias; details of which are skipped here due to brevity.

Figure 2. The accelerometer mounted on the forearm

Having the measurement data collected in the manner mentioned above, our first objective was to estimate the "typical" instantaneous acceleration, and determine how its uncertainty varies with the length of the observation period. In order to achieve this objective, we first need to find the appropriate duration of an observation period of acceleration data, and the number of such observation periods to sample. In terms of the observed amplitudes, each sample acceleration data provides a highly heterogeneous time series. Our approach to determine the shortest observation period is as follows.

First, partition each series into n_δ time intervals $I_{1,\delta},....,I_{1,n_\delta}$ of δ minutes each, and compute $m_{j,\delta}$ and $s_{j,\delta}$ as the median and MAD (Median Absolute Deviation) of the acceleration measurements made in interval $I_{j,\delta}$ for $j = 1,\ldots, n_\delta$. MAD denotes the median of the absolute deviations from the median, rescaled to match the standard deviation for Gaussian data. Second, let m_δ^* and s_δ^* denote the median and the MAD of the $\{ m_{j,\delta} \}$ whose corresponding $\{ s_{j,\delta} \}$ are greater than

---

[1] X6-1 is a product of Gulf Coast Data Concept, LLC. The X6-1 USB accelerometer has been used in this research to foster understanding. Such identification does not imply recommendation or endorsement by the National Institute of Standard and Technology, nor does it imply that this product is necessarily the best available for the purpose.

[2] Approval for use of human subjects in the course of this study has been documented in NIST IRB Case 358.

0.015 g. In this manner, m_δ^* summarizes the accelerations in those intervals where there is activity, indicated by some dispersion of measured accelerations in excess of a minimum threshold. This threshold can be defined based on the micro-generator architecture that is used to harvest enrgy. We repeated the steps just described for δ = 5, 6, 7,...., 120 minutes, one sample time series, thus obtaining a collection of 116 pairs of medians and MADs $\{(m_\delta^*, s_\delta^*)\}$ for each sample as depicted in the figure 4. The open circles in this Fig. 4 denote m_δ^*, and their values are presented along the left (black) vertical axis. At the same time, the red dots represent s_δ^*, and their values are displayed along the right (red) vertical axis.

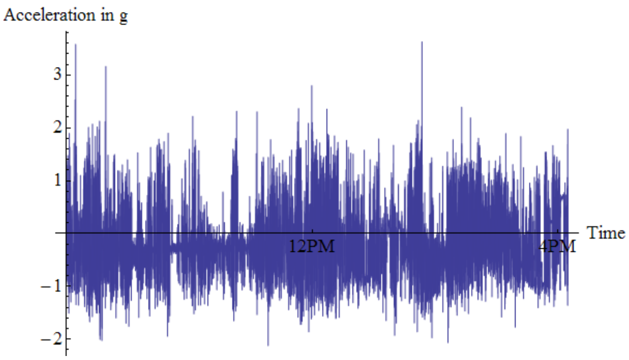

Figure 3. Sample acceleration measurements data (on the z axis)

The black curve summarizes how m_δ^* (the median of the selected interval medians corresponding to the partition into intervals of duration δ minutes) varies with δ. The red curve is a similar summary for s_δ^*. It exhibits the dispersion of the selected interval medians corresponding to the partition into intervals of duration δ minutes). For this sample, the median acceleration stabilizes at about 0.12 g for intervals whose duration is around δ = 40 minutes. The red curve suggests that, for these, the uncertainty of the interval median is around 0.09 g. The cloud of red dots also suggests that s_δ^* decreases roughly proportionally to $\sqrt{\delta}$, as one would expect from first principles. This implies that to cut that uncertainty of 0.09 g in half one will have to average the medians of the accelerations in four intervals of "typical" activity that are 40 minutes long. To achieve fair confidence in the second decimal place of the median acceleration (0.12 g), one should like to reduce this uncertainty to 0.009 g, for which purpose 100 such intervals will be needed.

In the above analysis, we used the median to reduce the influence of the extreme values in the data (i.e. outliers) on the result. However, when we repeated the above process with mean instead of median, no significant differences in the results were observed.

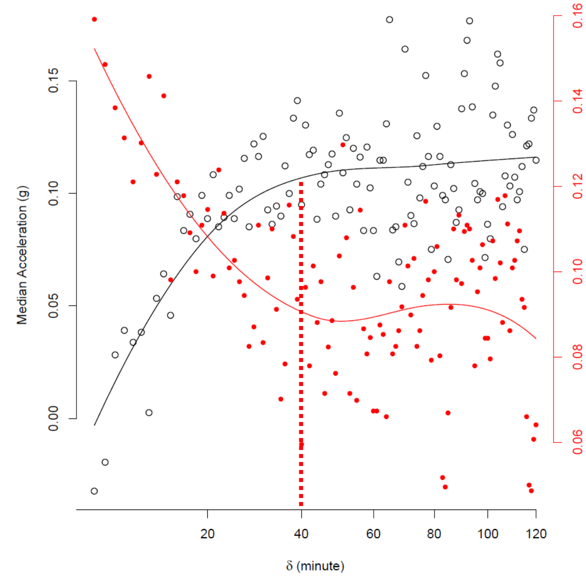

Figure 4. MAD and median versus time intervals

It should be noted that analyzed data corresponds to the z axis of the triaxial accelerometer which is perpendicular to the surface of the forearm. Visual inspection of the collected data demonstrated that this direction showed more activity compared to other axes (i.e. x and y which are parallel to the surface of the forearm). We also considered the magnitude of the acceleration (i.e. $\sqrt{a_x^2 + a_y^2 + a_z^2}$ where a_x, a_y, a_z are the acceleration along x, y and z axes respectively): in this case, the median acceleration stabilized around 1.02 g for 30 minutes intervals. In order to estimate the average generated power, we only used the z axis data, since there are currently no EH devices that can operate along all x, y, z directions at the same time.

We repeated the above analysis on data obtained through other individuals and concluded that 40 minutes is an appropriate size interval to observe stable median (or mean) acceleration. Using this result, figure 5 displays the distribution of the average acceleration for 480 such intervals (obtained from 40 test subjects). As observed, the distribution of these averages can be modeled by a Normal distribution with mean 0.1014 g and standard deviation 0.3247.

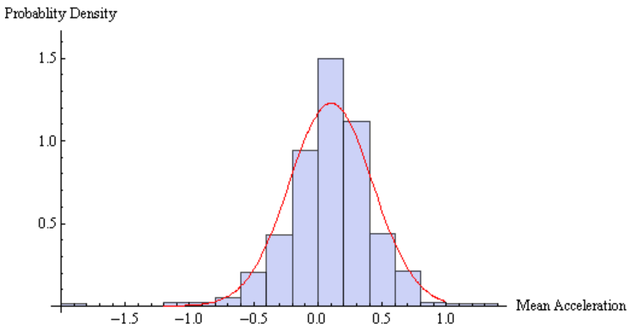

Figure 5. Histogram of average acceleration

III. ESTIMATION OF THE AVERAGE GENERATED POWER

The amount of harvested power depends on the intensity and the frequency of the acceleration as well as on the type of the micro-generator (i.e. EH) device. In this article we have focused on MEMs micro-generator harvesters that are based on inertial force. There are three types of architecture for inertial-based MEMS micro-generators, namely Velocity-Damped Resonant-Generator (VDRG), Coulomb-Damped Resonant-Generator (CDRG) and Coulomb-Force Parametric-Generator (CFPG) [3,8-9]. The first two architectures (i.e. VDRG & CDRG) are resonant generators where as the third one (i.e. CFPG) is a nonlinear generator that does not operate in a resonant manner.

The small physical scale of these micro-generators severely limits their efficiency (i.e. the ratio of the useful power output to the maximum possible output). Comparison of the efficiency of above three architectures has been done in [3,9]. The results show that CFPG has better performance when the device size is much smaller than the source motion amplitude. Also, more importantly, CFPG can operate effectively over a wide range of frequencies without the need for dynamic tuning. These two properties make CFPG architecture more attractive for wearable sensor applications. Therefore, we have chosen the equation compatible with the CFPG model to perform our analysis.

The approximate amount of harvested power is given by the following equation [9,10]:

$$p \approx \frac{1}{16} A_0 \omega \rho \alpha a^4 \qquad (1)$$

where $a \times a$ is the area of the generator, assumed to be a flat square, $\alpha \times a$ is the thickness ($\alpha < 1$), ω is the acceleration frequency, ρ is the proof mass density and A_0 is the maximum external acceleration [11]. For our analysis, we have used $a = 11mm$, $\alpha = 0.1$ and $\rho = 2\times10^4\ kg/m^3$ as suggested in [11]. In order to find the dominant frequency of the forearm motion, we have done a spectral analysis on our measurement data. Figure 6 shows a sample Fourier Transform of the acceleration for a 4 minutes interval.

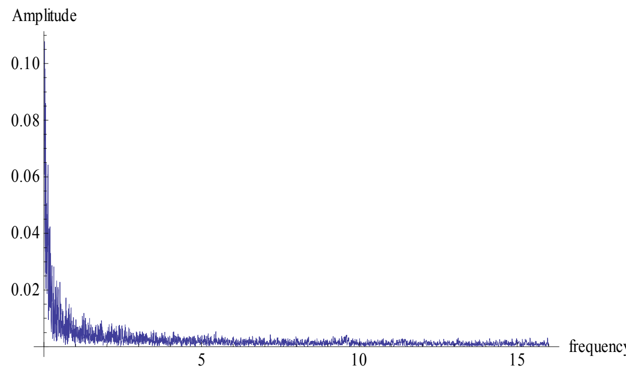

Figure 6. Sample Fourier transform for a 4-minute interval

As observed in equation (1), the amount of generated power depends on the product of the input acceleration frequency and its amplitude. Therefore, it is necessary to find the frequency under which we have the maximum occurrence of this product. To do this, we have divided the entire measurement data into periods of 4 minutes long and then performed Fourier analysis (with Kaiser filtering) on each segment. Then for each sample, we obtained the following:

$$Arg \max_f (A(f) \times f)$$

where $A(f)$ is the amplitude of the Fourier spectrum and f is the frequency. The histogram in Fig. 7 represents the distribution of the above frequencies. The frequency corresponding to the peak is around 1.95 Hz. This number determines the resonant frequency of the device and also points to the amplitudes that most effectively generate power by the micro-harvester. The average amplitude × frequency with peak occurrence (i.e. $f = 1.95$ Hz) is 5.25×10^{-3}. This will lead to an average estimated generated power of about 1.21μW. One should notice that the generated power is heavily dependent on the micro-generator device configuration (i.e. size and proof mass density). Other configurations might lead to different level of average power. Considering that the desired power consumption levels for wearable body sensors are in the micro-watt range, the estimated amount of average harvested power indicates that EH could be a promising technique for prolonging the lifetime of wearable medical sensors.

In the CFPG architechture, the proof mass is restrained by a holding force, and the work is only done when the acceleration is great enough to overcome this force. This holding force essentially defines a theshold for acceleration below which no energy is generated. We have used this threshold to study the temporal behavior of the accelartion. Details of this study which signifies a model for the interarrival time for meaningful levels of accelartion (and consequently power) has been omitted due to brevity.

IV. Conclusion and Future work

Our preliminary results show that the average harvested power by an inertial-based micro-generator is around 1.21μW. We have tried to use an acceleration input that is naturally generated by the human forearm motion. Average power of around 1 μW has also been reported in some recent publications [9]; however, their acceleration input data was generated under limited scenarios (i.e. 30 seconds of a uniform arm motion such as walking on a treadmill). Since many wearable medical sensors are envisioned to operate at the microwatt levels, such EH mechanism seems to be a promising technique in prolonging their operational lifetime or equivalently reducing their required frequency of recharge.

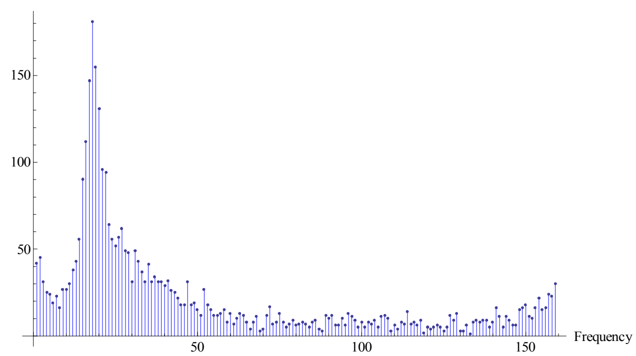

Figure 7. Histogram of frequencies where maximum amplitude×frequency occur

In this paper, we have focused on the forearm motion, however, the accelaration on some parts of the the lower body such as legs has higher intensity than upper body; therefore, it is expected that the amount of the harvestable enrgy is much larger at such lower body locations.

With the recent introduction of Body Area Networks (BAN) as a networked group of wearable or implantable sensors, temporal and spatial knowledge of the harvestable energy can be extremely useful in creating a power management model to efficiently correlate the computational need of the network with the generated power. However, there still exist many practical challenges such as the integration of the EH device with the electronics in the wearable sensors.

Also, longer measurement periods are also needed to accurately model the activity versus inactivity intervals (e.g. sleep or very low body activity). Further classification of data according to age, gender, body type etc could also be helpful in understanding the effectiveness of energy harvestig for different groups of people who could benefit from wearing medical sensors.

Acknowledgement

The authors would like to thank Ms. Alyssa Okita for her assistance in developing some of the codes necessary for the statistical analysis presented in this paper.

References

[1] Hayakawa M. “Electronic wristwatch with generator", Patent # 5001685, March 19, 1991, USA.

[2] M. Shiozaki, S. Sugiyama, N. Watanabe, H. Uenoand Itoigawa K., “Flexible thin-film BiTe thermopile for room temperature power generation”, IEEE 19th International Conf. on Micro Electro Mechanical Systems (MEMS 2006), Istanbul,.Jan. 2005, pp. 946-949.

[3] P.D. Mitcheson, E.M. Yeatman, G.K. Rao, A.S. Holmes. and, Green T.C., “Energy harvesting from human and machine motion for wireless electronic devices” IEEE Proc, Sept. 2008, Vol. 96, No.9, pp. 1457-1486.

[4] Q. Li, V. Naing, J.A. Hoffer, D.J. Weber, A.D. Kuo and, Donelan J.M., ”Biomechanical energy harvesting: apparatus and method”, Proc. Of IEEE International conference on Robotics and Automation (ICRA 2008) ,California, May 2008, pp. 3672-3677.

[5] N.S. Shenck and Paradiso J.A., “Energy scavenging with shoe-mounted piezoelectrics”. IEEE Micro, May 2001, Vol. 21 No.3, pp. 30-42.

[6] N. Ben Amor, O. Kanoun, A. Lay-Ekuakille, G. Specchia , G. Vendramin, and Trotta A.,” Energy harvesting from human body for biomedical autonomous systems”, Proc. Of the 7th IEEE conference on Sensors (Sensor 2008), Italy,Oct. 2008, pp. 678-680.

[7] C.V. Bouten, K.T.M. Koekkoek,M. Verduin,R. Kodde, and Janssen, J.D., “A triaxial accelerometer and portable data processing unit for the assessment of daily physical activity”, transaction on Biomedical engineering, Vol. 44, No.3, 1996, pp. 136-147.

[8] P.D. Mitcheson, T.C. Green, E.M. Yeatman and, A.S.Holmes, “Architecture for Vibration-Driven Micropoer Generators”, Journal of microelectromechanical systems, Vol. 13, No.3, June 2004, pp. 429-440.

[9] T.V. Buren, P.D. Mitcheson, T.C. Green, E.M. Yeatman, A.S. Holmes, and Troster G., “Optimization of Inertial Micropower Generators for Human Walking Motion”, IEEE Sensors journal, Vol. 6, No.1, Feb 2006, pp. 28-38.

[10] P. Miao, P.D. Mitcheson, A.S. Holmes, E.M. Yeatman, T.C. Green, and Stark B.H., ”Mems inertial power generators for biomedical applications”. Journal of Microsystem Technologies, Vol. 12, No. 10, Sept. 2006, pp. 1079-1083.

[11] P.D. Mitcheson,D.C. Yates,E.M. Yeatman, T.C. Green T.C., and Holmes A.S., “Modeling for optimization of self-powered Wireless Sensor nodes”, International Workshop on Wearable and Implantable Body Sensors Networks workshop (BSN 2005), United Kingdom, April 2005.