

Wrist actigraphy for scratch detection in the presence of confounding activities

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Abstract—Scratching is a symptom of many dermatological disorders, especially atopic dermatitis. For the development of anti-itch medications, there is a need for objective measures of scratching. Wrist actigraphy (monitoring wrist and hand movements with micro-accelerometers) is a promising method for assessing scratching; however, currently available technology has a limited capacity to discriminate scratching from other similar movements. In this study, we investigated methods to improve the specificity of actigraphy for scratch detection on movement data collected from subjects using the PAM-RL actigraph. A k -means cluster analysis was used to differentiate scratching from walking and restless sleep, which are potential confounds for nighttime scratching. Features used in the analysis include variance, peak frequency, autocorrelation value at one lag, and number of counts above $0.01\text{ g}'\text{s}$. The k -means cluster analysis exhibited a high sensitivity (0.90 ± 0.10) and specificity for walking (0.98 ± 0.05) and restless sleep (0.88 ± 0.06), respectively, demonstrating the separability of these activities. This work indicates that the features described here can be used to develop a classifier that discriminates scratch from other activities. The described method of scratch detection shows promise as an objective method for assessing scratching movements in clinical trials and longitudinal studies of scratch.

I. INTRODUCTION

CHRONIC itch is a burdensome condition frequently encountered in clinical medicine. It can be related to a wide variety of conditions including atopic dermatitis, scabies, and kidney failure. Scratch, the behavioral correlate of itch, can have significant negative consequences. Scratching is not only the result of itch, but also increases itch through the itch-scratch cycle [1]. Increased scratching causes local skin damage, resulting in infections and emotional distress due to visible sores [2]. Scratching frequently occurs at night and can undermine sleep [3]-[5], resulting in an increased mortality rate in kidney-dialysis patients suffering from chronic itch [6].

Furthermore, patients with skin diseases like atopic

dermatitis have a variable course where they undergo flares in the disease followed by remission. They also do most of their scratching at night while asleep and therefore are sometimes unaware that they are undergoing a severe bout until they have caused excessive skin damage. There is, therefore, particular interest in alerting patients to the emergence of severe bouts of scratching, allowing them to more effectively apply treatments. Earlier application of treatment may reduce the duration or severity of the bouts, allowing for higher sleep quality and quality of life [4], though children with atopic dermatitis experience sleep disorders even in remission [7].

In spite of the importance of timely treatment to reduce itch and scratching, few objective methodologies to optimally assess these treatments have been developed. An ideal approach would incorporate a device with several important characteristics. First, it would be usable in the subject's own home at night, better capturing typical behavior [8] and eliminating the cost of polysomnography—the current diagnostic technique [5]. Second, the device would be able to accurately detect scratch longitudinally (over a period of several nights). This is necessary because infrequent measurements do not allow for a complete characterization of the true state of the disease. Finally, the device would be easy and comfortable for the subject to use.

Wrist actigraphy, which records movements over time using micro-accelerometers, is convenient, wireless, user friendly, and can easily be worn for days at a time in the home environment. Actigraphy has been used as an indicator of scratching in several studies [9]-[13], but techniques developed to date do not allow differentiation of scratching from other movements such as walking [5]. The main reason for this is that current techniques estimate the amount of scratch in an overnight recording by generating a linear regression model between the number of activity counts in the 1-3 Hz range above a specific threshold and the total scratch time. However, other activities can confound this data, especially walking which also increases counts above threshold and has a frequency of 1 to 2 Hz. Getting up to use the bathroom during the night would therefore cause large discrepancies in the estimated proportion of scratching. This is especially problematic since nearly one third of Americans suffer from sleep-related disorders [14] that cause restlessness (and movements) at night unrelated to itch or scratch.

In this paper we propose an alternative approach to detecting scratch based on extracting a vector of four descriptive and possibly clinically relevant features from accelerometer data. We provide preliminary results showing that with a k -means clustering algorithm, these features are

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capable of separating periods of scratch from both walking and restless sleep. We demonstrate the successful separation using data obtained experimentally from twelve healthy subjects who simulated scratch, walked up and down a hallway, and simulated restless sleep. We conclude with a discussion of limitations of the proposed approach and future directions for both addressing these limitations and developing a classifier based on the proposed features to differentiate scratching from other nocturnal activities.

II. METHODS

A. Data Collection and Processing

A convenience sample of twelve adult subjects (8 male, 4 female, mean age 31 ± 5.2) were enrolled in the study, which was approved by the Institutional Review Board at Oregon Health and Science University (OHSU). Subjects were paid for their participation in the study. Tri-axial accelerometers (PAM-RL, Philips Respironics, OR, USA) were used for data collection. These accelerometers have a sampling frequency of 40 Hz, automatically bandpass filtered to 0.8-14 Hz.

The accelerometers were placed on the dominant wrist of each subject prior to the start of the test. Actigraphy data were collected for the following activities: (i) mimicking ‘restless sleep’: that is, lying still on the bed for 12 seconds, rolling to the right, and then holding still again, (ii) walking: specifically, walking to the end of a hallway, turning around and walking back to simulate the travel to and from the bathroom, and (iii) scratching: that is, scratching back of leg, crease of elbow, and head for 30s each. The data were then uploaded from the accelerometers onto a computer using DigiTrac software (IM Systems, MD, USA) and exported to Matlab (Mathworks, MA, USA) for further analysis. Because the output data from the accelerometers are triaxial, a new acceleration vector was created by averaging the x , y , and z acceleration vectors at each data point. This acceleration vector, $a(t)$ was used for further analysis.

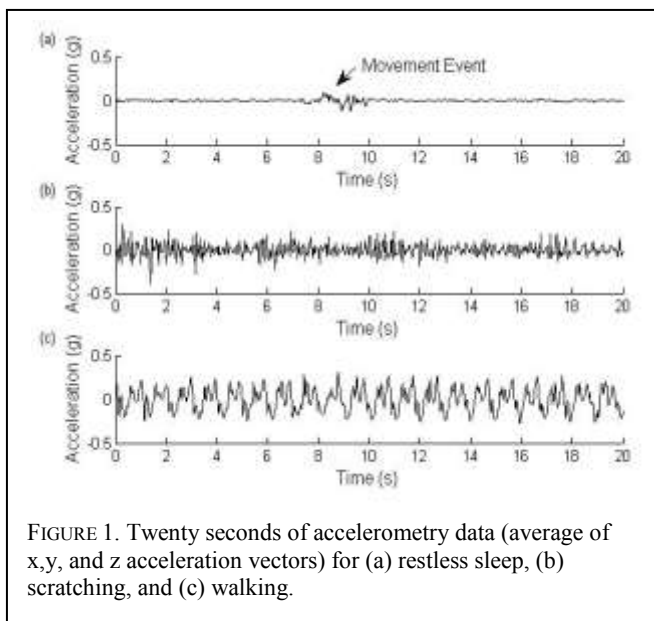


FIGURE 1. Twenty seconds of accelerometry data (average of x , y , and z acceleration vectors) for (a) restless sleep, (b) scratching, and (c) walking.

B. Feature Selection and K-Means Clustering

In order to implement the k -means cluster analysis, we first created epochs from which data features could be generated. We windowed the data using a window size (epoch length) of 3 seconds, and a step size of 2 seconds. Specifically, 120 data points were used to create each 3 second epoch, and each epoch overlapped the next by 40 data points (1 second). This window size was chosen to coordinate with previous scratch studies that defined ‘scratch’ as a bout of activity lasting 3 seconds or more [9] [15].

Once the epochs had been created, we used them to create the features used in the implementation of k -means. The features used for each epoch in this analysis were (i) number of counts above 0.01 g 's, (ii) the epoch variance, calculated as

$$s^2 = \frac{1}{n-1} \sum_{k=1}^n (a_k - \bar{a})^2 \quad (1)$$

where a_n is a data vector of length n , k is an integer value, and N was 4096, and (iv) autocorrelation value at one lag, given by

$$X(k) = \sum_{k=1}^N a_n e^{\frac{j2\pi(k-1)(n-1)}{N}} \quad (2)$$

where a_n is a data vector of length n , k is an integer value, and N was 4096, and (iv) autocorrelation value at one lag, given by

$$R_a(m) = \frac{1}{s^2} \sum_{k=0}^{N-m-1} a_{k+m} a_k \quad (3)$$

where a_{k+m} and a_k correspond to the value of the data at time $k+m$ and time k , respectively, N is the number of lags—in this case 10, and s^2 is the variance of the epoch which normalizes the vector so the autocorrelations at zero lag are equal to one. Each feature vector was normalized by subtracting its mean and dividing by the variance prior to implementation of the analysis. These features were chosen to capture the difference in amplitude and rhythmicity of scratching as compared to walking or restless sleep, as shown in Fig. 1. The analysis was performed for each subject separately due to differences in scratching and walking style between subjects.

K -means clustering segregates data into a pre-specified number of clusters k , by minimizing a cost function based on a suitable distance metric. In our implementation, we used the Euclidian norm, resulting in a cost function given by

$$J = \sum_{n=1}^N \sum_{k=1}^K r_{nk} \|a_n - \mu_k\|^2 \quad (4)$$

where r_{nk} represents a binary indicator that takes the value of one if a_n belongs to the cluster centered at μ_k and zero otherwise. The minimization of the cost function is solved by an iterative procedure consisting of a two-step process. Initial cluster centers are selected randomly from the available feature vectors during the initialization of the algorithm. Next, each data point is assigned to its closest center, forming early groups. New cluster centers are then calculated as the mean of the data points assigned to a given

cluster. This cycle continues until the calculated cluster centers no longer change. For a more detailed explanation, see [16].

III. RESULTS AND DISCUSSION

Prior to implementation of the k -means analysis, all epochs were labeled according to their actual activity. Because the k value, which specifies the number of clusters the data will be divided into, must be specified a-priori, we tested the performance of several k values. We chose to test k values of 3, 4, and 5 because we have at least 3 activities to differentiate (scratching, walking, and restless sleep), and at most 5 activities, considering the different types of scratching.

To compare k values to each other, we calculated the sensitivity, and specificity of the test. To do this, all epochs in a given cluster were assigned an activity value based on the percent of each activity (as labeled a-priori) in that cluster. For example, if a given cluster contained mostly scratching, all epochs in that cluster would have a ‘test prediction’ of scratch. Because the k -means cluster analysis is guaranteed to find a local, but not necessarily global, minimum, we ran the test five times for each subject and then averaged the results. We also calculated the sensitivity and specificity of the test when running the data from all subjects simultaneously to ensure the generalizability of the results.

Table I shows the sensitivity (number of true scratching epochs correctly identified as scratch divided by total number of scratching epochs), specificity to walk (number of walking epochs correctly identified as walking divided by total number of walking epochs), and specificity to restless sleep (number of restless sleep epochs correctly identified as restless sleep divided by total number of restless sleep epochs), of the test when performed for each individual separately as well as for all individuals as a whole.

While a k -value of 5 gave the highest overall sensitivity, it is interesting to note that decreasing k resulted in lower sensitivity to scratch. This is probably due to differences in the scratch style between head, leg, and elbow scratching. Head scratching tended to be high amplitude and highly rhythmic, similar to walking. Leg and arm scratching, on the other hand, tended to be lower amplitude and less rhythmic,

TABLE I. Sensitivity, specificity and accuracy of the k -means test in distinguishing scratch from walking and restless sleep. While $k=5$ had highest sensitivity and accuracy, $k=3$ had highest specificity in distinguishing scratch from walk.

k		Sensitivity	Specificity (Walk)	Specificity (Sleep)
3	Ind	0.67 ± 0.27	0.98 ± 0.06	0.83 ± 0.13
	All	0.78 ± 0.19	0.99 ± 0.03	0.91 ± 0.06
4	Ind	0.84 ± 0.18	1.00 ± 0.00	0.90 ± 0.05
	All	0.82 ± 0.20	0.94 ± 0.10	0.90 ± 0.06
5	Ind	0.90 ± 0.10	0.99 ± 0.05	0.88 ± 0.06
	All	0.89 ± 0.16	0.85 ± 0.31	0.89 ± 0.04

TABLE II. Results of the k -means cluster analysis for $k=5$. Each value corresponds to the average number of epochs of each activity that were identified as a given activity based on 5 trials per subject.

		Actual Activity			Total
		Scratch	Walk	Restless Sleep	
Test Prediction	Scratch	487	2	9	498
	Walk	50	118	12	180
	Restless Sleep	3	0	159	162
Total		540	120	180	840
Sensitivity (%)		90	98	88	

more similar to restless sleep. Thus, as k decreased, head scratching was more easily confused as walking; leg and arm scratching were more easily confused as restless sleep.

Furthermore, the sensitivity and specificity of the analysis varied between subjects. For example, the specificity of distinguishing scratch from walking for subject 12 was only 0.65, while that for subject 5 was 1.0 (data not shown). The main difference between subjects was the amplitude and rhythmicity of scratching; while the classification for low amplitude, random scratching was very sensitive, more rhythmic and higher amplitude scratching tended to be confused with walking. In such cases, increasing the number of clusters dramatically improved sensitivity since some types of scratching were more separable. It is also interesting to note that the analysis had decreased specificity to walk when all the data was clustered together. This is probably because there were fewer walking samples than either scratching or restless sleep (120 compared to 180 and 540, respectively). Grouping the data together therefore caused the scratching samples to pull the cluster centers away from the walking data, as shown in Figure 2. While it is clear that these activities are separable using these features, the cluster analysis has difficulty performing when the amount of data is imbalanced. Because the k -value of 5 was found to give

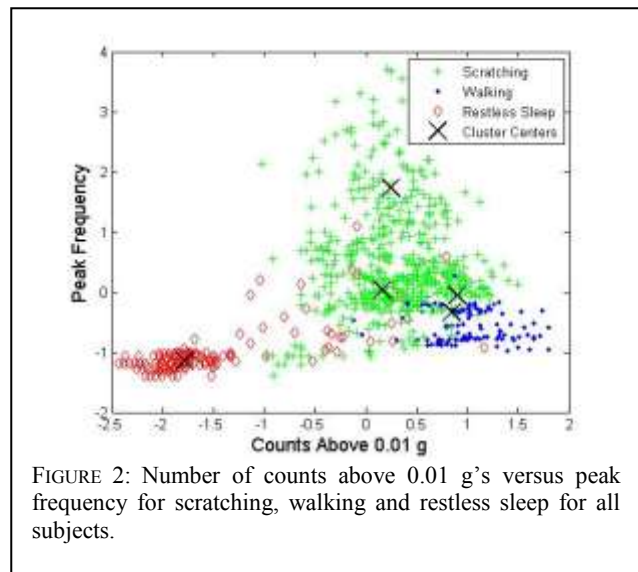


FIGURE 2. Number of counts above 0.01 g's versus peak frequency for scratching, walking and restless sleep for all subjects.

the highest sensitivity overall, it was used for further analysis.

Table II shows a confusion matrix for the k -means cluster analysis for $k = 5$. The analysis correctly identified scratch 90% of the time. The test also correctly distinguished scratch from walking 98% percent of the time and scratch from restless sleep 88% of the time. It is important to note that the majority of misclassified restless sleep activities belonged to the movement event. However, as k decreased, these activities were more likely to be misclassified as walking than as scratching. Therefore, if these feature vectors are applied to a binary model, we expect the specificity with respect to the movement event, specifically, to increase.

All subjects were instructed to scratch, but were not actually itchy. Future work will determine the efficacy of this algorithm for subjects who are actually itchy. Specifically, we plan to test the analysis method for atopic dermatitis patients wearing the actigraph overnight. We believe that in this population, scratching may be much higher amplitude and lower frequency and as a result may more closely resemble walking. Therefore, the specificity in distinguishing scratch from walking in a clinical population may not be as high as that reported here for healthy subjects. However, if this is the case, the specificity in distinguishing scratch from restless sleep is predicted to increase as the method never confused walking with restless sleep. The proposed method is a dramatic improvement on current scratch-sensing methods.

V. CONCLUSIONS

Although current actigraphy-based scratch-sensing methods can provide an estimate of amount of scratching overnight, they are not able to specifically identify periods of scratching. For both clinical and research applications, a technique for specifically identifying scratching would represent a significant advance. Using the feature set we propose (variance, frequency, autocorrelation value at one lag, counts above 0.01 g's), we have extended the actigraphy-based methods of current approaches to scratch detection. We also provide a more precise indication of true scratching behavior in the face of confounding activities. This is evidenced by the high level of separation between scratching, restless sleep, and walking.

The method is most applicable at night, when the majority of movements are either restless sleep or scratching. While subjects scratch most at night, future work will look at using this analysis method to distinguish scratching from other day-time activities. This would generate the most accurate picture of scratching in the itchy population, and therefore may be quite useful in determining effective treatment methods.

It is important to note that the k -means algorithm segregates activities determined a-priori. For example, in this case we knew the test data consisted of only scratching, walking, and restless sleep. In clinical trials, however, specifying all the activities that could occur during a recording is very challenging. Still, the k -means analysis shows that the specified feature set can be used to separate walking, scratching and restless sleep. Therefore future work

will be devoted to using these features to build a classifier that can either separate scratch from walking, restless sleep, and 'other', or possibly a binary classifier that can distinguish scratch from all other activities.

Despite these limitations and because of the high sensitivity (0.90) and specificity of the proposed method, we believe the feature based method of scratch detection will be suitable for use in both clinical trials and longitudinal studies of scratch.

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VII. REFERENCES

- [1] D. Camfferman, J. D. Kennedy, M. Gold, A. J. Martin, and K. Lushington, "Eczema and sleep and its relationship to daytime functioning in children," *Sleep Med Rev*, vol. 14, pp. 359-69.
- [2] L. R. Daud, M. E. Garralda, and T. J. David, "Psychosocial adjustment in preschool children with atopic eczema," *Arch Dis Child*, vol. 69, pp. 670-6, 1993.
- [3] K. L. Hon, M. C. Lam, T. F. Leung, C. M. Chow, E. Wong, and A. K. Leung, "Assessing itch in children with atopic dermatitis treated with tacrolimus: objective versus subjective assessment," *Adv Ther*, vol. 24, pp. 23-8, 2007.
- [4] P. T. Thorburn and R. L. Riha, "Skin disorders and sleep in adults: where is the evidence?," *Sleep Med Rev*, vol. 14, pp. 351-8, 2010.
- [5] R. Sack and J. Hanifin, "Scratching below the surface of sleep and itch," *Sleep Med Rev*, vol. 14, pp. 349-50.
- [6] G. Miller, "Biomedicine. Grasping for clues to the biology of itch," *Science*, vol. 318, pp. 188-9, 2007.
- [7] H. Reuveni, G. Chapnick, A. Tal, and A. Tarasiuk, "Sleep fragmentation in children with atopic dermatitis," *Arch Pediatr Adolesc Med*, vol. 153, pp. 249-53, 1999.
- [8] H. A. Molenaar, J. Oosting, and E. A. Jones, "Improved device for measuring scratching activity in patients with pruritus," *Med Biol Eng Comput*, vol. 36, pp. 220-4, 1998.
- [9] B. G. Bender, R. Ballard, B. Canono, J. R. Murphy, and D. Y. Leung, "Disease severity, scratching, and sleep quality in patients with atopic dermatitis," *J Am Acad Dermatol*, vol. 58, pp. 415-20, 2008.
- [10] K. Benjamin, K. Waterston, M. Russell, O. Schofield, B. Diffey, and J. L. Rees, "The development of an objective method for measuring scratch in children with atopic dermatitis suitable for clinical use," *J Am Acad Dermatol*, vol. 50, pp. 33-40, 2004.
- [11] T. Ebata, S. Iwasaki, R. Kamide, and M. Niimura, "Use of a wrist activity monitor for the measurement of nocturnal scratching in patients with atopic dermatitis," *Br J Dermatol*, vol. 144, pp. 305-9, 2001.
- [12] K. L. Hon, M. C. Lam, T. F. Leung, W. Y. Kam, K. C. Lee, M. C. Li, T. F. Fok, and P. C. Ng, "Nocturnal wrist movements are correlated with objective clinical scores and plasma chemokine levels in children with atopic dermatitis," *Br J Dermatol*, vol. 154, pp. 629-35, 2006.
- [13] C. Bringham, K. Waterston, O. Schofield, K. Benjamin, and J. L. Rees, "Measurement of itch using actigraphy in pediatric and adult populations," *J Am Acad Dermatol*, vol. 51, pp. 893-8, 2004.
- [14] S. Ancoli-Israel and T. Roth, "Characteristics of insomnia in the United States: results of the 1991 National Sleep Foundation Survey. I," *Sleep*, vol. 22 Suppl 2, pp. S347-53, 1999.
- [15] T. Aoki, H. Kushimoto, Y. Hishikawa, and J. A. Savin, "Nocturnal scratching and its relationship to the disturbed sleep of itchy subjects," *Clin Exp Dermatol*, vol. 16, pp. 268-72, 1991.
- [16] C. M. Bishop, "Pattern Recognition and Machine Learning." New York: Springer Science+Business Media, LLC, 2006.