Energy and Accuracy Trade-Offs in Accelerometry-Based Activity Recognition

Ning Wang, Geoff V. Merrett, Robert G. Maunder and Alex Rogers

Electronics and Computer Science

University of Southampton

Southampton, UK

{nw7g08, gvm, rm, acr}@ecs.soton.ac.uk

***Abstract*—Driven by real-world applications such as fitness, wellbeing and healthcare, accelerometry-based activity recognition has been widely studied to provide context-awareness to future pervasive technologies. Accurate recognition and energy efficiency are key issues in enabling long-term and unobtrusive monitoring. While the majority of accelerometry-based activity recognition systems stream data to a central point for processing, some solutions process data locally on the sensor node to save energy. In this paper, we investigate the trade-offs between classification accuracy and energy efficiency by comparing on- and off-node schemes. An empirical energy model is presented and used to evaluate the energy efficiency of both systems, and a practical case study (monitoring the physical activities of office workers) is developed to evaluate the effect on classification accuracy. The results show a 40% energy saving can be obtained with a 13% reduction in classification accuracy, but this performance depends heavily on the wearer's activity.**

Keywords—activity recognition; body sensor networks; classification accuracy; energy efficiency

I. Introduction

Society is witnessing an increase in chronic disease and age-related illnesses, and this is coupled with an increasing demand for cost-effective, yet high quality, healthcare. As a result, delivery models are changing radically from professional-centric systems to distributed networked systems [1]. Typical examples include systems gathering information on patients in their own homes [2]–[4]. A further trend is a transition from managing illness to maintaining wellness [5], through monitoring daily activity to prevent obesity or encourage lifestyle change. In such applications, activity recognition systems can provide cost-effective, continuous and real-time monitoring of an individual's physical context.

Accelerometry-based activity recognition systems typically consist of one or more sensor nodes mounted on the body, which communicate with a central point to form a body sensor network. Recent research has demonstrated the recognition of many physical activities, with systems using a single accelerometer providing cost effective solutions for recognizing simple activities [6]–[8]. Systems utilizing multiple sensors usually demonstrate greater accuracy, but are more costly, inconvenient and uncomfortable [9]. Furthermore, different sensor locations result in varying abilities to classify different activities. Co-recognition systems [10] allow recognition of both activity and sensor location, rendering the need for prior information on sensor placement redundant.

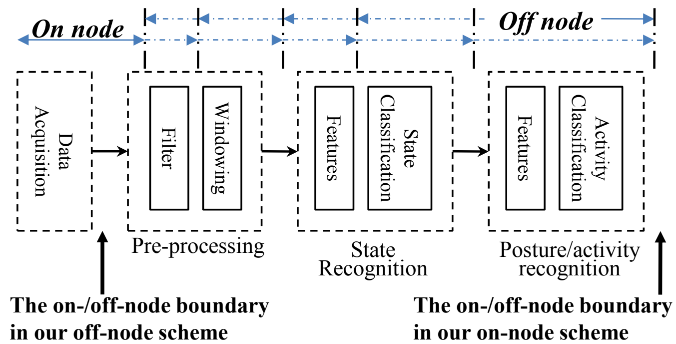

Fig. 1. Stages in an activity recognition system. The labels above the diagram show *potential boundaries* between on- and off-node classification schemes, while the labels below show the *boundaries used in this paper*.

Most existing research, such as that discussed above, has focused primarily on improving the classification performance of systems 'off-node', where sensor nodes make measurements and send data for processing and classification at a central point. As transmission is commonly regarded as the largest consumer of energy [11], research has also considered moving some, or all, data processing tasks to the sensor nodes [12]. Such 'on-node' schemes can reduce the amount of data transmitted, and are thus typically assumed to be more energy-efficient [13]. However, such simple analysis of the trade-offs between on- and off-node systems may not always be correct. On-node schemes make additional demands on the sensor node, such as computational processing, and these can be a significant consumer of energy. To date, a detailed investigation of these trade-offs has not been presented.

To address this shortcoming, in this paper we report on a detailed comparison between on- and off-node classification schemes, and evaluate the trade-offs between energy efficiency and classification performance. Section II provides a detailed discussion on the distinction between on- and off-node activity recognition schemes, while Section III presents an empirical energy model developed to jointly investigate the energy consumption of sensing, communication and data processing. Section IV describes a case study scenario of monitoring an office worker's daily physical activities. A practical implementation of this case study has been developed, and details are given of both the hardware and software algorithms. Our results in Section V show that, while on-node schemes can permit significantly lower energy consumption (we demonstrate a 40% reduction), the magnitude depends on the wearer's activities, and is at the expense of accuracy.

II. On- and Off-Node Activity Classification

Activity classification using accelerometers involves a number of stages, most of which are common among different implementations; illustrated in Fig. 1. In general, after raw acceleration data are acquired from sensors, these are pre-processed (e.g. applying digital filtering and windowing) to improve later processing. One or more features (which can be obtained in the time- and/or frequency-domain) are then calculated. These features are subsequently used as inputs to a classification algorithm which maps data to a specific activity. Research efforts have proposed variations and extensions to this process, for example the use of a 'divide-and-conquer' strategy [9], [13]. This strategy involves recognition of basic 'states' (e.g. sedentary or active states) at a low level, followed by detailed analysis of a specific activity (e.g. sitting, standing or walking) at a higher level. Such classification methods simplify recognition and enhance classification accuracy.

As highlighted above, data processing operations can be divided into a number of distinct tasks. Potentially, most tasks could be performed locally on the sensor node (on-node processing) or at the central sink node (off-node processing). The boundary between on- and off-node schemes is not unique, and could be drawn in many places (illustrated at the top of Fig. 1). For example, one on-node scheme could transmit features for classification off-line, while an alternative could perform classification on-node and simply transmit classified activities. In this paper, the distinction between on- and off-node schemes is as follows (illustrated at the bottom of Fig. 1):

- **Off-node classification:** the sensor node acts as a data collector, acquiring and transmitting data at a fixed rate.
- **On-node classification:** the sensor node acquires and pre-processes data, obtains features, and classifies states, posture and activities on-node. Transmissions only occur when a different activity is classified. Data acquisition sample rates are dynamically reduced during sedentary postures (e.g. sitting/standing) and increased for dynamic activities (e.g. walking/running).

Dynamic sampling is possible with the on-node scheme because the node has information about the currently classified activity. While the central point in the off-node scheme could communicate this information back to the sensor node, this would require nodes to listen for packets (causing an additional energy cost and reducing the maximum sample rate). More significantly, the sensor node would need to perform local processing to identify when the sample rate subsequently needed to be increased. Hence, such a system becomes a hybrid scheme between the extremes considered here.

A trade-off typically exists between on- and off-node classification schemes. For example, off-node schemes are more computationally capable, yet require a lot of energy to transmit all raw data. On-node schemes compress transmitted data by locally generating features or even classifying activities. However, in addition to limited computation capability (e.g. limited memory, operations per second, access to floating point units) which can reduce accuracy, a trade-off is created between the energy required to process and transmit data, impacting on the overall energy-efficiency.

III. Energy Modeling

To investigate the effect of both on- and off-node schemes on energy efficiency, an energy consumption model is derived. This model is subsequently used to evaluate our case study (Section V) using empirically obtained parameter values.

$$E(t) = E_M(t) + E_T(t) + E_S(t) \tag{1}$$

Energy is considered to be consumed by three subsystems: sensing, processing and communication. The total energy consumed, $E(t)$, at time t is given by (1), where E_M, E_T and E_S are the energy consumed by the microcontroller, radio transceiver and sensor respectively. Each is detailed below.

A. Data Acquisition

The sensing subsystem consists of the accelerometer and ADC. In our scenario, the accelerometer is constantly powered while the ADC is active only during sampling. Therefore, its energy consumption is modeled by (2), where P_M is the power consumption [W] of the accelerometer, P_{Aa} and P_{As} are the power consumption [W] of the ADC in active and sleep modes respectively, and α_A represents the duty cycle of the ADC.

$$E_S(t) = \left(P_M + P_{Aa}\alpha_A + P_{As}(1-\alpha_A)\right)t \tag{2}$$

As the duty cycle of the ADC depends only on the sample rate S [Hz], the duty cycle of off-node $\left(\alpha_A^{off}\right)$ and on-node (α_A^{on}) schemes can be expressed by (3) and (4) respectively:

$$\alpha_A^{off} = nS \tag{3}$$

$$\alpha_A^{on} = n\sum_i S_i\rho_i \tag{4}$$

where n is the active time [s] of the ADC during each sample, S_i is the sample rate [Hz] used when the current activity (which has a probability ρ_i of occurring) has been classified as activity i, and $S \leq 1/n$. Therefore, provided that sample rates used in the on-node scheme are always equal to or lower than the off-node scheme, the duty cycle/energy consumption will always be lower for the on-node scheme.

B. Radio Transceiver

The transceiver's energy consumption is modeled by (5), where P_{Ta} and P_{Ts} are mean power consumptions [W] of the radio transceiver in active and sleep modes respectively, and α_T represents the duty cycle of the radio transceiver.

$$E_T(t) = \left(P_{Ta}\alpha_T + P_{Ts}(1-\alpha_T)\right)t \tag{5}$$

Similar to the above, the duty cycle of the radio transceiver in the off-node scheme is given by (6), where m is the average time [s] required to transmit one data sample, and $S \leq 1/m$.

$$\alpha_T^{off} = mS \tag{6}$$

The on-node scheme only transmits a classification result when it changes. Therefore, the transceiver's duty cycle, which is not related to the sample rate, is expressed by (7), where τ is the time [s] to transmit a data packet containing a classification result, μ is the average activity change rate [Hz], and $\mu \leq 1/\tau$.

$$\alpha_T^{on} = \tau\mu \tag{7}$$

As acceleration data are captured at a higher sample rate in the off-node scheme, data transmission typically occurs several times per second resulting in a high α_T^{off}. In the on-node scheme however, α_T^{on} is determined by the rate of activity change μ, which is typically less than 0.01 Hz. Therefore, significant energy savings can be obtained using an on-node scheme. However, if the individual being monitored changes activity frequently, the energy consumed by the transceiver in the on-node scheme will approach the off-node scheme.

C. Data Processing

The total energy consumed by the microcontroller is expressed by (8), where P_{Ma} and P_{Ms} are power consumptions [W] of the microcontroller in active and sleep modes respectively, and α_M is the duty cycle of the microcontroller.

$$E_M(t) = \left(P_{Ma}\alpha_M + P_{Ms}(1-\alpha_M)\right)t \tag{8}$$

In the off-node scheme, the microprocessor is active only to transmit a predetermined number of samples. Therefore the duty cycle α_M^{off} (9) is proportional to the sample rate S, where k is the average time [s] spent active for each sample (including time spent acquiring data from the ADC and controlling the transceiver during transmission), and $S \leq 1/k$.

$$\alpha_M^{off} = kS \tag{9}$$

In the on-node scheme, the microcontroller must be active to process and transmit data; its duty cycle α_M^{on} is given by (10), where k_i is the time [s] taken to obtain features and perform classification when the current activity is activity i.

$$\alpha_M^{on} = \tau\mu + \sum_i k_i S_i \rho_i \tag{10}$$

From (10), it can be seen that the duty cycle is formed of two parts: that required for data transmission (equivalent to (7)), and that required for data processing (similar to (4)). Due to the greater computational load, k_i is typically 5-15x times greater than k (illustrated in the case study in the next section). Although the on-node scheme's sample rate varies, $\sum k_i S_i \rho_i$ is always greater than kS, hence the microcontroller consumes more energy in the on-node scheme than the off-node scheme.

D. Discussion

If we ignore the (usually negligible) energy consumed in sleep modes, the overall consumption of the off- and on-node schemes can be simplified to (11) and (12) respectively.

$$E_{off}(t) = (P_M + P_{Ma}k + P_{Ta}m + P_{Aa}n)St \tag{11}$$

$$E_{on}(t) = \left(P_M + P_{Ma}\left(\sum_i k_i S_i \rho_i + \tau\mu\right) + P_{Ta}\,\tau\mu + P_{Aa}\,n\sum_i S_i\rho_i\right)t \tag{12}$$

The energy consumption of the off-node scheme is varied only by the sample rate, while the on-node scheme is dependent on S_i, ρ_i and μ – i.e. rendering it heavily dependent on the individual's activities. To further investigate the energy consumption of the two schemes, and to evaluate their effect on classification accuracy, the next section presents a case study. The results (Section V) presented from the case study utilize the energy model presented here, using empirically obtained parameters for power consumptions and active times.

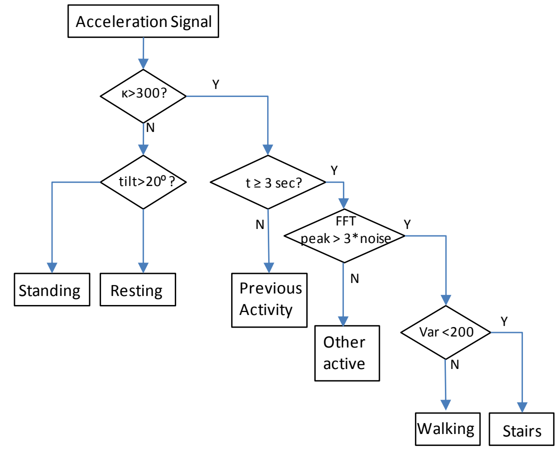

Fig. 2. The classification algorithm used in the case study.

IV. CASE STUDY: OFFICE WORKER WELLBEING

Office workers are prone to obesity [14], creating a motivation for unobtrusive and easy-to-use systems for real-time activity recognition. For an office worker who spends many hours sitting in a chair, it is beneficial to classify and calculate the length of time which they are sedentary, to help avoid leading a sedentary lifestyle. In our case study, a typical office scenario is chosen, and a single body-worn accelerometer used to classify postures and activities. The classified states and activities include sedentary states (standing or resting – e.g. sitting or lying), and dynamic states (walking, using stairs, or other 'dynamic' activities). Walking is considered a 'lifestyle exercise' and, as a relatively simple lifestyle change to make, and through information on duration and step rate, wearers can gain useful lifestyle information.

The sensor nodes were developed using the Texas Instruments eZ430-RF2500 development tool, containing a low-power MSP430 microcontroller and 2.4-GHz wireless transceiver. The microcontroller has a variable clock and low-power sleep modes, enabling power consumption to be minimized. The node is constrained by processing speed, limited on-chip RAM (1 KB) and lack of floating-point unit. Acceleration data are sampled via a 10-bit ADC that can be operated while the microcontroller is in a sleep state. Acceleration data were sampled using a triaxial accelerometer (Analog Devices ADXL335) with a measurement range of ±3 'g' (where 'g' = 9.81 ms^{-2}). Data are transmitted wirelessly using the SimpliciTI communication protocol, and are received by the sink node. After it is powered on, the sink waits for a sensor node to join the network, and then listens for packets. The sensor is attached to the front of the subject's thigh.

A. Classification Algorithm

Although on-node classification is constrained by limited on-chip resources, it shares the same classification algorithm with the off-node scheme. We developed a threshold-based classification algorithm, based on Mathie's framework [15], which exploits knowledge on the activities to be classified using a hierarchical binary decision tree. The tree used to implement the process illustrated by Fig. 1, is shown in Fig. 2.

1) State Recognition: The first step is to determine whether the activity is sedentary or active. Active states are defined as extended or repetitive activities, e.g. walking or climbing stairs, while minor, short or slow activities such as changing position in a chair or transients from sitting to standing are ignored. The signal magnitude area (SMA) feature [15] is widely used to distinguish between sedentary and active states, but requires computationally expensive filtering to remove gravitational components in each axis. Furthermore, the gravitational components cannot be completely removed as they partially overlap with the frequencies of human movement (0-20 Hz). In this research, a feature κ is used which sums the absolute difference between each two consecutive acceleration samples in each axis every second (13), where N is the window length [samples] set such that it represents 1 s of data, i.e. $N = S$ (constrained due to memory limitations). Our experiments indicated this is a good indication of state, and is effective in our scenario as most activities are 'powered' by the thigh. An appropriate threshold value for κ is experimentally determined such that, when κ is above it for at least 3 s, the preceding period is considered to represent an active state.

$$\kappa = \sum_{j=1}^{N-1} |x_j - x_{j+1}| + \sum_{j=1}^{N-1} |y_j - y_{j+1}| + \sum_{j=1}^{N-1} |z_j - z_{j+1}| \quad (13)$$

2) Classifying Sedentary Postures: A distinction between standing and resting is made by considering the tilt angle (θ) between the thigh (y-axis) and the vertical (14) [13], [15].

$$\theta = \arccos(y) \quad (14)$$

3) Classifying Dynamic Activities: Once a state is considered active, dynamic activities are considered. Due to their periodicity, a Fast Fourier Transform (FFT) is performed over a window of y-axis acceleration data to identify the associated frequency components. The y-axis is used as it was found to best identify the use of stairs when compared to x- and z-axes. To further distinguish stairs from walking, a threshold is applied to the variance of the acceleration data. Due to RAM limitations and a lack of on-board floating point unit, fixed point computation is used for both filtering and FFT calculation, reducing the accuracy of the on-node scheme.

4) Adaptive Data Acquisition: In our on-node scheme, we exploited the fact that people typically spend less than 15% of their time performing dynamic activities [16] by implementing adaptive data acquisition. By thresholding κ, the sample rate remains low (10 Hz) for the majority of the time, only increasing (40 Hz) during dynamic activities.

V. Results and Discussion

Results were obtained from the case study detailed in the previous section. The test subject was asked to repeat a sequence of activities, defined in Table I, three times. These were chosen to mimic common activities found in an office environment. Acceleration data and classification results were wirelessly transmitted in real-time to a sink node connected to a laptop. The laptop displayed acceleration data and classification results (both calculated on-node and off-node in MATLAB). The software also allowed an 'annotator' to follow the test subject and manually annotate the data with ground truth changes in context. Start and end flags were manually added to the data to allow time synchronization.

TABLE I. Sequence of Activities used in the Case Study

ID	Activity	Approx. duration (s)
1	Sit on sofa	15
2	Stand	10
3	Walk to stairs	20
4	Walk up stairs	45
5	Walk to office	20
6	Open door	3
7	Walk to desk	6
8	Sit down	15
9	Stand up, walk to door	6
10	Open door	3
11	Walk to stairs	20
12	Walk down stairs	42
13	Walk to sofa	10
14	Sit down	15

A. Classification Accuracy

Fig. 3 shows the acceleration data and classification results (on-node, off-node and ground truth) for one of the three obtained activity sequences. Acceleration in the y-axis (along the thigh) is shown, as it is used in classifying all activities. To evaluate the results, the ground truth is compared with classified activities. For every second where the ground truth matches the classified activity, a correct outcome is recorded (and vice-versa). Classification accuracy was calculated as the fraction of time in which activities were correctly classified.

Tables II and III show confusion matrices for both off-node and on-node classification schemes. The results obtained reveal the ability of the system to distinguish between sedentary postures and dynamic activities and to recognize sitting and standing with a high degree of accuracy. The ability to classify walking was somewhat lower, though acceptable results were produced for both on- (88%) and off-node (80%) schemes.

TABLE II. Confusion Matrix Showing the Classification Results for the Off-Node Scheme (Units: Seconds).

		Actual Activity					**Classified Activity is Correct**
		Resting	***Standing***	***Walking***	***Stairs***		
					Up	***Down***	
Classified Activity	***Resting***	160	0	0	0	0	100%
	Standing	3	60	4	2	0	89%
	Walking	0	0	297	3	0	99%
	Stairs	0	0	31	114	87	86%
	Other Activity	0	0	5	6	31	0%
Activity Correctly Classified		98%	100%	88%	83%		94% / 89%

TABLE III. Confusion Matrix Showing the Classification Results for the On-Node Scheme (Units: Seconds).

		Actual Activity					**Classified Activity is Correct**
		Resting	***Standing***	***Walking***	***Stairs***		
					Up	***Down***	
Classified Activity	***Resting***	160	0	0	0	0	100%
	Standing	3	60	4	2	0	89%
	Walking	0	0	270	4	0	98%
	Stairs	0	0	33	102	15	78%
	Other Activity	0	0	18	17	103	0%
Activity Correctly Classified		98%	100%	80%	48%		93% / 76%

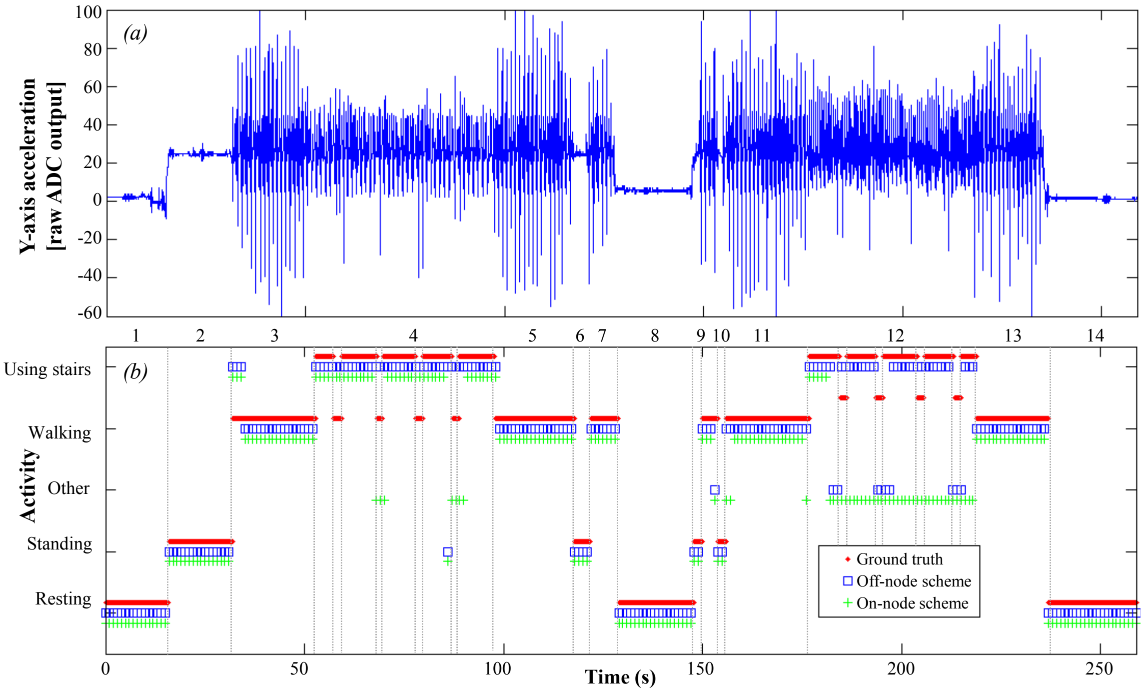

Fig. 3. Results obtained showing (a) acceleration data in the y-axis, and (b) classification results obtained from one dataset. The classification results show on-node (green) and off-node (blue) classifications and ground truth activities (red). Vertical dashed lines separate the different activities (the specific activities are identified by the IDs listed in Table I) performed according to the ground truth.

The ability of the system to classify the use of stairs showed a considerable difference between off- and on-node schemes, with the on-node scheme performing significantly worse (48% rather than 83%). The classification of dynamic activities, including walking and using stairs, performed worse on- than off-node due to the less accurate FFT (Section IV). It should be noted however that the purpose of the case study is not to suggest a novel algorithm for classification, rather to compare off- and on-node schemes. Clearly improvements are required in classifying the use of stairs, for example by using an additional accelerometer at a different location on the body.

B. Energy Consumption

The energy model (Section III) was used to evaluate the energy consumption of both schemes, using parameters obtained from empirical measurements and datasheets. This enabled a single node to collect data which performed both on- and off-node classification, with the energy consumption calculated afterwards. In-situ energy measurement would have required two nodes with power monitoring circuitry to be worn by the subject, making the setup more cumbersome (impeding normal movement) and non-identical sensor placement (hence classifying activities based upon different acceleration data).

To validate our energy model, the power consumption of a sensor node running the off-node scheme was measured. Data were obtained using an Agilent N6705B DC Power Analyzer, allowing accurate seamless measurement of both sleep and active currents, and analysis of the results. Fig. 4 shows the power consumption of a single transmission cycle. The node's behavior can be clearly seen, showing periodic sampling (30 measurements, representing 10 samples of each axis of a triaxial accelerometer) between transmissions. The energy consumption of a single transmission cycle was measured as 0.619 mJ (mean power of 2.56 mW over 0.242 s). The period needed for 10 samples illustrates the inaccurate clock on the node, resulting in a 41.3 Hz sample rate instead of 40.0 Hz. Comparing these with our energy model gives an error of just 0.1% (our model predicted 0.620 mJ; 2.48 mW over 0.25 s).

To further analyze the energy consumption of both schemes, we performed a Complementary Cumulative Distribution Function (CCDF) of the current consumption, allowing inspection of how much time the node spends in different power states. More specifically, the CCDF indicates the percentage of time that the node draws at least x mA. Three setups were used: off- and on-node schemes with a single sedentary posture, and the on-node scheme with both sedentary and dynamic activities. For each setup, measurements were obtained for 30 s. The resulting CCDFs are shown in Fig. 5.

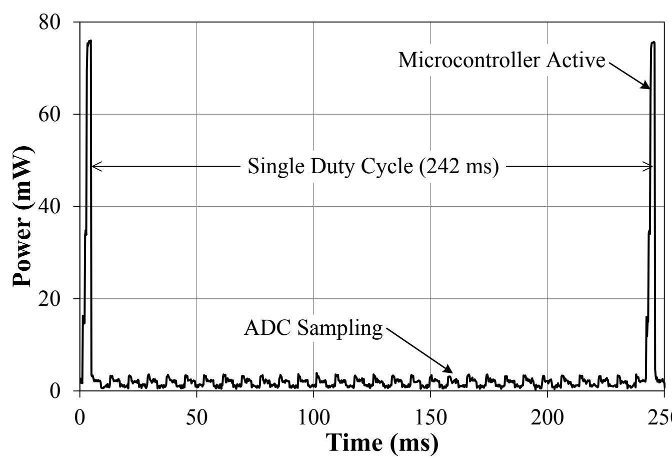

Fig. 4. Power consumption of a single transmission cycle of a node running the off-node scheme.

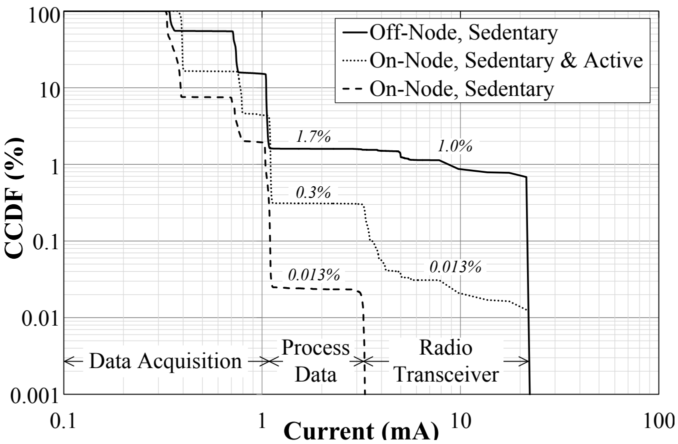

Fig. 5. Complementary Cumulative Distribution Function (CCDF) of the current consumption for sensor nodes implementing different setups of the off- and on-node approaches.

The off-node setup (where current consumption is independent of the wearer's activities), consumes >1mA (data processing and communication tasks) for only 1.7% of the time. Communication tasks are represented by the 0.7% of time that the node consumes >20mA). Comparing this with the on-node sedentary setup, the node consumes >1 mA for only 0.013% of the time – an order of magnitude lower than the off-node scheme. Furthermore, as the node never transmits, the maximum consumption is only 3 mA. The on-node sedentary and active setup is a more typical example, where the node is classifying both sedentary and dynamic activities during the 30 s period. The benefits of the on-node scheme can clearly be seen as it spends only 0.3% of the time consuming >1 mA.

TABLE IV. ESTIMATED ENERGY CONSUMPTION OF BOTH ON- AND OFF-NODE SCHEMES USING THE DEVELOPED ENERGY MODEL

Function	Average power consumption	
	Off-node	***On-node***
Data processing	0.13 mW	0.40 mW
Radio transceiver	0.59 mW	0.01 mW
Data acquisition	1.76 mW	1.08 mW
Total	2.48 mW	1.49 mW
Normalized total	100%	60.1%

Using our energy model, the energy consumed by the nodes in our case study was calculated for both on- and off-node schemes; Table IV. On-node classification has reduced energy consumption by 40% scheme, and it can be seen that it consumed more energy processing data, yet made greater savings through reduced communication (only transmitting activity changes) and data acquisition (adaptive sampling). Comparing accuracy and energy results, the on-node scheme reduced consumption by 40% while reducing accuracy by 13%. Reduced accuracy particularly affected classification of stair use, a non-trivial task using a single accelerometer. Energy consumption is highly dependent on the activity performed. If the wearer stays in an active state, the on-node scheme may consume more energy than off-node through increased data processing. Likewise, if the wearer changes activity very often, energy consumed through communication would be significantly increased. However, in most cases, the energy consumed for the on-node scheme will be much lower. Over a longer experiment, average consumption would likely be much lower as people typically spend >85% of their time in sedentary states [17], as opposed to 28% in our case study.

VI. CONCLUSIONS

This paper has investigated the trade-offs between classification accuracy and energy efficiency of on- and off-node activity recognition schemes. An experimentally validated energy model was developed to illustrate and analyze energy consumption. A case study is considered to evaluate the schemes, and a practical system developed. The results show the on-node scheme is as accurate as off-node for classifying sedentary postures, but less accurate for dynamic activities due to hardware limitations. A 13% reduction in accuracy permitted a 40% reduction in energy consumption; but, such results are shown to depend heavily on the wearer's activity.

REFERENCES

[1] Codagnone, C., in Reconstructing the Whole: Present and Future of Personal Health Systems, Information Society and Media Directorate-General, European Commission, 2009, pp. 6.

[2] Chan, M., Estève, D., Escriba, C. and Campo, E., "A review of smart homes-present state and future challenges," Comput. Methods Prog. Biomed., vol. 91, pp. 55-81, 2008.

[3] Helal, S., Mann, W., El-Zabadani, H., King, J., Kaddoura, Y. and Jansen, E., "The Gator Tech smart house: a programmable pervasive space," Computer, vol. 38, pp. 50-60, 2005.

[4] Rashidi, P. and Cook, D. J., "Keeping the resident in the loop: adapting the smart home to the user," IEEE Trans. Systems, Man and Cybernetics, Part A: Systems and Humans, vol. 39, pp. 949-959, 2009.

[5] Dishman, E., "Inventing wellness systems for aging in place," Computer, vol. 37, pp. 34-41, 2004.

[6] Yang, J.-Y., Wang, J.-S. and Chen, Y.-P., "Using acceleration measurements for activity recognition," Pattern Recognition Letters, vol. 29, pp. 2213-2220, 2008.

[7] Jin, G. H., Lee, S. B. and Lee, T. S., "Context awareness of human motion states using accelerometer," J. Med. Syst., vol.32, pp.93-100, 08.

[8] Khan, A. M., Lee, Y. K. and Kim, T. S., "Accelerometer signal-based human activity recognition using augmented autoregressive model coefficients and artificial neural nets," in Int'l Conf. IEEE Engineering in Medicine and Biology Society (EMBS'08), 2008.

[9] Fang-Chen, C., Jeen-Shing, W., Ya-Ting, Y. and Tzu-Ping, K., "A wearable activity sensor system and its physical activity classification scheme," in Int'l Conf. Neural Networks (IJCNN), 2012.

[10] Wenyao, X., Mi, Z., Sawchuk, A. A. and Sarrafzadeh, M., "Co-recognition of human activity and sensor location via compressed sensing in wearable body sensor networks," in Int'l Conf Wearable and Implantable Body Sensor Networks (BSN'12), 2012.

[11] Raghunathan, V., Schurgers, C., Sung, P. and Srivastava, M. B., "Energy-aware wireless microsensor networks," IEEE Signal Processing Magazine, vol. 19, pp. 40-50, 2002.

[12] Stäger, M., Lukowicz, P. and Tröster, G., "Power and accuracy trade-offs in sound-based context recognition systems," Pervasive and Mobile Computing, vol. 3, pp. 300-327, 2007.

[13] Karantonis, D. M., Narayanan, M. R., Mathie, M., Lovell, N. H. and Celler, B. G., "Implementation of a real-time human movement classifier using a triaxial accelerometer for ambulatory monitoring," IEEE Trans. Inf. Technol. Biomed., vol. 10, pp. 156-167, 2006.

[14] Juneau, C.-E. and Potvin, L., "Trends in leisure-, transport-, and work-related physical activity in Canada 1994-2005," Preventive Medicine, vol. 51, pp. 384-386, 2010.

[15] Mathie, M., "Monitoring and interpreting human movement patterns using a triaxial accelerometer," Ph.D. dissertation, Faculty of Eng., Univ. of New South Wales, 2003.

[16] Lader, D., Short, S. and Gershuny, J., "The Time Use Survey," The Office of National Statistics, 2006.