Saving Energy on Wrist-Mounted Inertial Sensors by Motion-Adaptive Duty-Cycling in Free-Living

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***Abstract*— This paper presents a motion-adaptive approach to duty-cycling of the orientation estimation using a Madgwick filter on an inertial measurement unit (IMU). Specifically, a proportional forward-controller was employed to dynamically tune the sampling and orientation update rate of a Madgwick filter. An energy model was defined to estimate power consumption of individual sensors and processing elements. We demonstrate the efficacy of our controller by analysing free-living motion recordings of wrist-worn IMUs with sparse relevant events. The orientation estimation at a full duty-cycle is compared with the adaptive one. The average estimation error was kept around 10 degrees while saving more than 30% of energy. To evaluate the orientation estimation error, we applied a pattern classification of food and fluid intake gestures. The recognition performance remained robust up to an energy saving of approx. 30%.**

I. Introduction

A main obstacle to deploy body-worn sensor-based wearable systems in free-living is the limited runtime. Battery life of many current miniature accessory and garment systems can barely cover one day. A continuous long-term behavioural monitoring system requires energy to sample sensor data, to store or transmit data, to perform on-line processing, data abstraction and, in some application, interaction with the user. Furthermore, the processing of multimodal or multisource context information in modern mobile systems increases computational load, turning into higher energy consumption. Deriving solutions to mitigate the powering problem has became quickly a priority in many fields.

Phenomenologically, the majority of target events in monitoring systems' sensor data patterns are sparse in time. In fact, interesting events in social, physical or physiological environment, are spaced out by long period of 'uninteresting' activities. Continuous sampling is then, evidentially, not an optimal approach. The dilemma is how to effectively trading-off between quality of information, by sampling relevant phenomena from the environment, and saving on-board energy, by ignoring irrelevant ones. One potential energy management strategy is to actively change the duty-cycle of the sensing system [1]. The sensor is kept in sleep mode most of the time and active state is requested in response to some interesting activity.

In this paper, we present a motion-adaptive approach to duty-cycling orientation estimation using a Madgwick filter (MF). We focused on hand and arm motion, as they are considered in many applications of Inertial Measurement Unit (IMU) systems. In particular, we analysed IMU systems worn at the wrist, e.g. in a smart watch. We applied a controller to an inertial sensing and orientation processing system to continuously tune the estimation quality. When the system was affected by rotation, the orientation estimation rate increased, up to the maximum system sampling rate. In contrast, if there was no rotation affecting the system, sampling and processing rates were both reduced. During these sub-maximum duty-cycles, energy was saved.

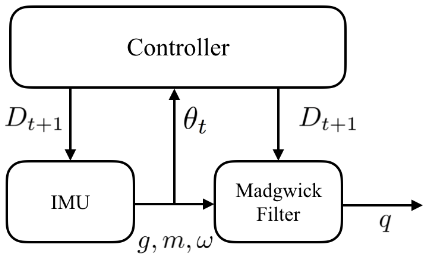

Fig. 1: Schematic of our motion-adaptive orientation estimation system. Data from accelerometer (g), magnetometer (m), gyroscope (ω) were used to derive quaternion coordinate estimates q by the MF. The proportional control input θ_t is feed-forwarded into the duty-cycle rate controller. The controller provides a rate output (D_{t+1}) that controls IMU sampling rate and MF processing rate.

We provide the following contributions:

1) We present our lightweight power controller and motion-adaptive method to duty-cycle the IMU sampling and MF orientation estimation rates.
2) We evaluated energy costs and energy savings of a sensor node's sampling and processing stages in a system simulation. Performances regarding the trade-off between quality of information and energy consumption were evaluated by exploiting two basic information metrics, i.e., quaternion estimation error and accuracy performance of a gesture recognition task.

II. Related Work

To reduce energy consumption, many different software approaches have been designed, including power on-time reduction [2], computation reduction [3] and communication reduction [4]. An extensive analysis of power-aware wearable and mobile systems was recently provided by Rault et al. [5]. We based our investigation on results presented by Derungs et al. [1]. The authors implemented a motion adaptive approach to duty-cycle

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the IMU sampling and an orientation estimation rate of an extended Kalman filter, demonstrating the energy saving potential of the method. Here we investigate a different orientation estimation filter, i.e., MF, analyse data from a free-living scenario, and implement a sensor node energy simulation to analyse sampling and processing-related energy consumption.

III. Methods

A. Motion Sensing Inertial Measurement Unit

An IMU is used to estimate orientation by measuring and fusing acceleration, angular rate, and magnetic field. In our approach, the duty-cycle of the sensor node is tuned dynamically by the controller via a control signal D. We followed the one-shot measure paradigm, i.e., the sensor wakes up, takes a sample, and goes to sleep again. The active state duration t_{act} comprises wake-up and sampling time (approximated as instantaneous).

The standby state has duration t_{stby} that depends on the duty-cycle rate. The duty-cycle is expressed as:

$$\text{Period} = \frac{t_{\text{act}}}{D} \tag{1}$$

For instance, for period $= 70$ ms and active state period $t_{act} = 35$ ms, the duty cycle will be $D = 50\%$.

B. Proportional Controller

We adopted a similar design to the one tested by Derungs et al. [1]. A feed-forward proportional controller accepts a proportional control input derived by the angular rate ω from the gyroscope sensor. The proportional control input was chosen as:

$$\theta_t = |\omega_{x,t}| + |\omega_{y,t}| + |\omega_{z,t}| \tag{2}$$

where θ is the control input and t is the time-step.
A linear mapping function converts θ to D:

$$D_{t+1} = D_l + \left[\frac{D_h - D_l}{\theta_h - \theta_l} \cdot \theta_t - \theta_l\right] \tag{3}$$

where D_l is the minimum duty-rate, set at the threshold θ_l, that was estimated from the gyroscope sensor noise. A maximum duty-rate D_h was set at a threshold θ_h. Both D_h and D_l are system design parameters and different values for them can be selected. An example is provided below.

C. Madgwick Filter

The MF is an efficient orientation filter for inertial and inertial/magnetic sensor arrays. The filter is based on a gradient-descent algorithm and is designed to process accelerometer, gyroscope and magnetometer data by using a quaternion representation. Detailed description of the algorithm can be found in Madgwick et al. [6]. The MF processing rate was tuned via the controller duty-cycle rate output. Output of the MF is a time-series of quaternions q that represent orientation. Computationally, we derived that the MF MARG implementation requires about 280 arithmetic operations per filter update, which includes the magnetic distortion and gyroscope drift compensation.

D. Simulation

To evaluate the costs and cost-savings of a real hardware case scenario, we considered a hypothetical wearable node and its components. In Tab. I, components of the considered sensor node are presented with their specifications. Dependencies among different components, and between hardware and software, needed to be correctly reproduced. Thus, we implemented the simulation platform introduced by Buschhoff et al. [7], a component-based hardware description approach in which any component of the system was described by a state machine.

E. Power Consumption Model

In our framework, each node element has a power consumption component:

$$P_{\text{node}} = \sum_{\text{i}}^{\text{N}_s} P_{\text{i}} + P_{\text{mcu}} + P_{\text{store}} \tag{4}$$

where $N_{\text{s}} = 3$ is the number of sensors, P_{i} is the sensor's power consumption, P_{mcu} is the microcontroller unit's power consumption and P_{store} is the power consumption for writing data on a SDcard. For the analysis in this work, P_{store} was kept constant.

1) Sensor Power Consumption: Fig. 2 depicts the simplified current consumption profile of the sensor device during a single measurement cycle. The current consumption profile switches between two states. In active state, the sensor consumes an average current I_{act} for a duration t_{act}. In standby state, the current I_{stby} is mainly consumed by the digital circuitry of the sensor for a duration t_{stby}. When using the device in power saving, i.e., $D < 1$, we approximated the average current consumption using the following equation:

$$I_{\text{p}} = I_{\text{act}} \times D + I_{\text{stby}} \times (1 - D) \tag{5}$$

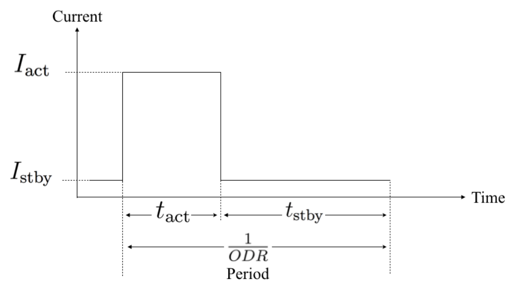

Fig. 2: Simplified current consumption model used in the simulation. The current profile switches between two stages, i.e., active and standby. Phases of the sensor activation as regulator charge, boot-up and measurement are characterised by an average active current, i.e., I_{act}.

2) Microcontroller Unit Power Consumption: The average power consumption of the microcontroller was modelled as:

$$P_{\text{mcu}} = t_{\text{proc}} P_{\text{mcu}_{\text{act}}} + (t_{\text{tot}} - t_{\text{proc}}) P_{\text{mcu}_{\text{low}}} \tag{6}$$

We deliberately neglected the amount of power consumed by the microcontroller during period of transition

Component	Manufacturer	Model	$t_{\text{wu}}[ms]$	$I_{\text{act}}[\mu A]$	$I_{\text{stby}}[\mu A]$	V	$E_{\text{con}}[mWh]$	$E_{\theta_{\text{h}}}[mWh]$
Accelerometer	InvenSense	from MPU-9250	20	450	8	2.5	61.1	13.4
Gyroscope	InvenSense	from MPU-9250	35	3200	8	2.5	434.2	145.6
Magnetomer	AKM	AK8963 from MPU-9250	50	280 (8Hz)	3	2.5	38.0	27.0
Microcontroller	Texas Inst.	TI MSP430F1611	/	2380	2.31	3.701	8.4	2.1
SD-Card	SanDisk	SD2Gb	/	4460	/	3.701	895.6	895.6

TABLE I: Components of the simulated sensor node and their specifications. t_{wu}: wake-up time interval duration. I_{act}: average current consumption in active mode. I_{stby}: average current consumption in standby mode. V: voltage. E_{con}: average (among participants) energy consumption in continuous sampling mode. E_{θ_h}: average (among participants) energy consumption in motion-adaptive duty-cycling mode. SD-Card power P_{store} was kept constant.

between active state and low-power mode. The period t_{proc} is proportional to the clock cycles required for reading the sensors data, estimate orientation and generate the control signal. In our simplified model, the time of an algorithm execution is roughly estimated as follows:

$$t_{\text{proc}} = \frac{n_{\text{m}} + n_{\text{a}}}{f_{\text{mcu}}} \tag{7}$$

where n_{a} is the number of cycles for additions per iteration, n_{m} is the number of cycles multiplications per iteration, and f_{mcu} is the clock frequency of the microcontroller, i.e., 3.69 MHz for the TI MSP430F1611. Deriving the number of clock cycles per operation is not a trivial task. We interpret the addition and multiplication as output of the multiply-accumulate operation and define a loose upper-bound of 12 cycles per operation.

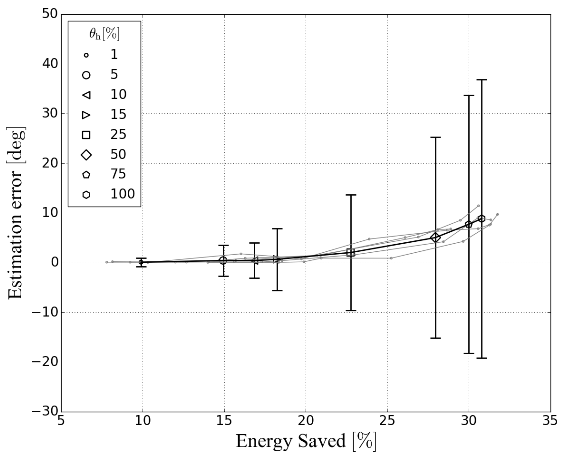

Fig. 3: Average estimation error mean and error standard deviation over energy saved while varying controller sensitivity. Grey lines represent performance for individual participants. Parameters: $D_{\text{h}} = 1$, $D_{\text{l}} = 0.1$, $\theta_{\text{h}} = 364$, $\theta_{\text{l}} = 3$.

F. *Daily Life Activity Data Collection*

Six healthy volunteers (2 females, 4 males) aged between 20 and 40 years wore two Shimmer wireless IMU sensors attached to their wrists during normal daily routine for about five days. Participants were generally healthy with normal BMI. The sensors were attached using a stretchable band in the morning after getting up and kept on the body until bed time. The sensors were detached if a risk of contamination with water existed. Participants were asked to maintain a paper diary of their activities, in particular their dietary behaviour. The average monitoring duration per participant was 49.2 hours, with an average 0.53 hours per participant spent in food intake-related gestures. To evaluate the proposed motion-adaptive duty-cycling, right hand IMU data were considered.

IV. Evaluation Methods

In order to validate the energy saving potential of the motion-adaptive controller, we evaluated the estimation approach with two information metrics.

A. *Quaternion Estimation*

The quality of orientation estimation can be evaluated by comparing the orientation estimation at a full duty-cycle with the one computed by adaptive duty-cycling. A unit quaternion implies that **q** and **-q** indicates the same 3D rotation. To take into account the ambiguity in quaternion representation, we used the pseudometric called *inner product of unit quaternion* [8], shown in Eq. 8.

$$\begin{aligned} &\Phi : S^3 \times S^3 \rightarrow \mathbb{R}^+, \\ &\Phi(\mathbf{q}_1, \mathbf{q}_2) = 1 - |\mathbf{q}_1 \cdot \mathbf{q}_2| \end{aligned} \tag{8}$$

Function Φ gives values in the range [0, 1] that can be converted in range [0, 180] degrees.

B. *Gesture Recognition*

To further evaluate the controller, we analysed a gesture recognition task. Binary isolated classification between fluid intake gestures and a set of food intake gestures, including fork intake, spoon intake and hand intake, was performed while varying the controller sensitivity. Gestures were represented as 16 time series, i.e., triaxial accelerometer, gyroscope and magnetometer data, Tait-Bryan angles, precession, nutation and spin. Each gesture was divided in four temporal segments. From each segment several statistical features were extracted. A forward selection algorithm for feature selection was applied and eight features were selected. A personalised model was built for each participant using support vector machine classifiers. A 5-fold cross-validation scheme was applied to evaluate the models.

	P1	P2	P3	P4	P5	P6
Fluid intake	84	154	139	164	279	129
Food intake	473	579	490	403	374	289

TABLE II: Number of instances for the two classes of intake gestures considered in the gesture recognition evaluation. Each column refers to one participant $[\mathrm{P}_1, \ldots, \mathrm{P}_6]$.

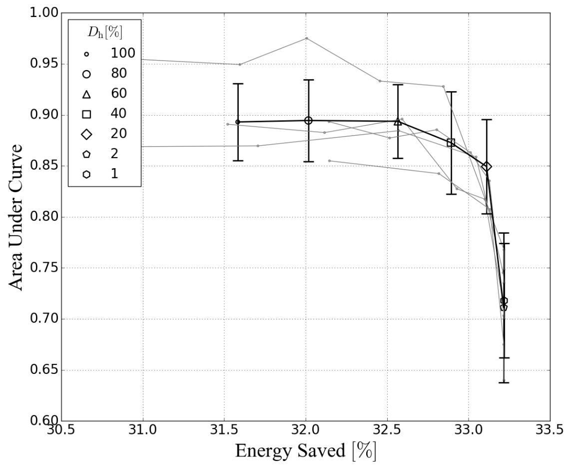

Fig. 4: Average gesture recognition's area under curve by tuning the maximum duty-rate. Grey lines correspond to performance on individual participant data. Parameters: $D_\mathrm{h} = 1$, $D_\mathrm{l} = 0.01$, $\theta_\mathrm{h} = 364$, $\theta_\mathrm{l} = 3$.

V. Results

The last two columns of Tab. I report average total energy consumption for continuous E_{Con} and motion-adaptive duty-cycle E_{θ_h} modes. The contribution of the SD-card to the total power consumption was kept constant and independent of the sampling rate.

Fig. 3 shows the inner product of quaternion over the amount of energy saved in the gesture segments. The sensitivity of the controller was tuned by changing the θ_h value. It is evident that energy can be saved while maintaining an acceptable quality of orientation estimation. Specifically, in all conditions, the average estimation error remains under ten degrees while more than 30% of energy is saved.

Fig. 4 shows the classification performance over the energy saved. The result indicates that the gesture recognition could be carried out without performance deterioration up to an energy saving of approx. 32.5%.

VI. Conclusion

In this work, a method to save energy on wrist-mounted inertial sensors was presented. We describe our light-weight proportional forward controller that tunes the duty-cycle of the sensor depending on the rotation activity performed by wearers. An energy model to estimate the amount of power consumption of the sensor node elements was implemented. We tested our estimation procedure in free-living by simulating the sensor node, revealing highly promising results.

Further studies are required to evaluate variables that may affect the energy consumption, including type of activities, sensor's body position, user characteristics, e.g., gender, BMI, and age.

Our approach can save energy and thus increase runtime or reduce battery size in wearable systems. Sparsity in relevant events is a key assumption in our approach to maintain duty cycle $D < 1$. While many applications in behaviour and environmental analysis suit here, energy savings may be reduced for constant cyclic activities, such as cycling or running. We believe that our approach could be extended to slow-rate sensor measurement modes to address cyclic activities too.

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References

[1] A. Derungs, H. Lin, H. Harms, and O. Amft, "Motion-adaptive duty-cycling to estimate orientation using inertial sensors," in *Pervasive Computing and Communications Workshops (PERCOM Workshops), 2014 IEEE International Conference on*, pp. 47–54, IEEE, 2014.

[2] T. Park, J. Lee, I. Hwang, C. Yoo, L. Nachman, and J. Song, "E-gesture: a collaborative architecture for energy-efficient gesture recognition with hand-worn sensor and mobile devices," in *Proceedings of the 9th ACM Conference on Embedded Networked Sensor Systems*, pp. 260–273, ACM, 2011.

[3] R. Cilla, M. A. Patricio, A. Berlanga, and J. M. Molina, "Creating human activity recognition systems using pareto-based multiobjective optimization," in *Advanced Video and Signal Based Surveillance, 2009. AVSS'09. Sixth IEEE International Conference on*, pp. 37–42, IEEE, 2009.

[4] U. Maurer, A. Smailagic, D. P. Siewiorek, and M. Deisher, "Activity recognition and monitoring using multiple sensors on different body positions," in *Wearable and Implantable Body Sensor Networks, 2006. BSN 2006. International Workshop on*, pp. 4–pp, IEEE, 2006.

[5] T. Rault, A. Bouabdallah, Y. Challal, and F. Marin, "A survey of energy-efficient context recognition systems using wearable sensors for healthcare applications," *Pervasive and Mobile Computing*, vol. 37, pp. 23–44, 2017.

[6] S. O. Madgwick, A. J. Harrison, and R. Vaidyanathan, "Estimation of imu and marg orientation using a gradient descent algorithm," in *Rehabilitation Robotics (ICORR), 2011 IEEE International Conference on*, pp. 1–7, IEEE, 2011.

[7] M. Buschhoff, C. Günter, and O. Spinczyk, "A unified approach for online and offline estimation of sensor platform energy consumption," in *Wireless Communications and Mobile Computing Conference (IWCMC), 2012 8th International*, pp. 1154–1158, IEEE, 2012.

[8] D. Q. Huynh, "Metrics for 3d rotations: Comparison and analysis," *Journal of Mathematical Imaging and Vision*, vol. 35, no. 2, pp. 155–164, 2009.