Poster: BlueSense - Designing an Extensible Platform for Wearable Motion Sensing, Sensor Research and IoT Applications

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Abstract

We present an extensible sensor research platform for wearable and IoT applications. The result is a 30x30mm platform capable of 500Hz motion and orientation sensing using 98mW when logging the data. The platform can wake up at programmed intervals using only 70uW in hardware off mode. A maximum 0.6ppm time deviation between nodes allows usage in a network for whole body movement sensing.

1 Introduction

Our work is motivated by sensor-based human activity recognition which is key to smart-assistive systems. It addresses issues we experienced in prior work collecting large scale datasets for human activity recognition [7] and takes into account experiences reported by other researchers. The key observations are: i) some applications require real-time recognition and thus data streaming, whereas others perform offline analysis which requires data logging; ii) multiple sensors are generally improving recognition performance, thus their recordings must be synchronised [4]; iii) using limb coordinates instead of raw motion data is well suited for fine gesture recognition, which thus requires orientation sensing [8]; iv) some applications require high sample rate, especially in sports [2]; v) activity recognition can benefit from novel sensors [5], and thus a platform should be extensible.

A secondary motivation is measurements over extended periods of time at low sample rate (e.g. once per day), which is common in Internet of Things (IoT) applications. Instead of hardware event detectors [9] we combine true hardware off with programmed wake-up through a real-time clock.

2 Hardware

The platform (fig. 2) comprises an ATmega1284p microcontroller at 11MHz, 3V regulator and LiPo battery charger, Micro SD slot, a single-chip 3D accelerometer, gyroscope and magnetometer (MPU9250), a coulomb counter, and USB and Bluetooth 2 interfaces. Classic Bluetooth allows enough bandwidth for real-time analytics. It has a one of the highest accuracy real-time clock (RTC) on the market (DS3232M), with ±5 ppm accuracy over the entire temperature range. It is used to timestamp the recordings of independent nodes. We measured the drift of the RTC to be less than 0.6ppm when nodes are at room temperature. Overall, the platform is 30x30mm. It accepts extension boards on top or bottom (fig. 1). One connector comprises the programming interface, SPI interface, regulated power, USB power, two GPIO which can also be used as ADC inputs, and an open-drain line which can be used to wake up the system from hardware off. This may be used to implement event detectors using low-power analog circuitry [9]. The other connector comprises the I2C interface, analog and battery power and 5 GPIO pins, 3 of which can be used as ADC inputs.

True hardware off is achieved by turning off the power regulator (LTC3553 in fig. 2). The system can wake up from this mode when the power button is pressed, when a real-time clock alarm occurs, or when a pin on the expansion connector is pulled low. The logic to wake up the system (power logic in fig. 2) is powered by the battery directly.

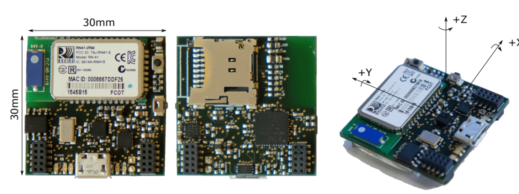

Figure 1. PCBs and node fitted with a 160mAh battery. Larger batteries can be employed if needed.

3 Firmware

The firmware offers a terminal interface over USB and Blueooth to setup the node and start/stop data acquisition. We designed the firmware to achieve high sample rate with low jitter. No operating system is used to minimise overheads. However a comprehensive library abstracts the user application from the hardware details. Most I/O library functions rely on interrupt routines to exchange data with peripherals. The interrupt routines stores or reads the data from memory buffers to which the library functions called from user code can also access. The SD card interface however is not interrupt driven and SD card writes are blocking.

International Conference on Embedded Wireless
Systems and Networks (EWSN) 2018
14–16 February, Madrid, Spain

ISBN: 978-0-9949886-2-1

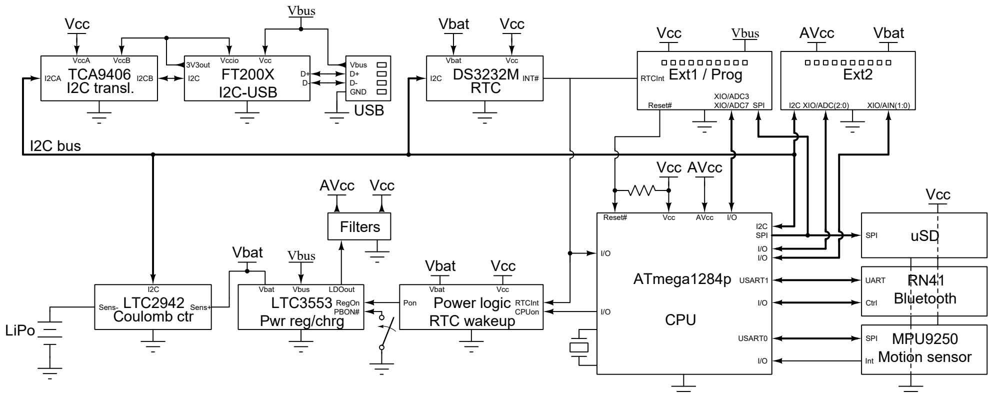

Figure 2. Extensible sensing platform for wearable and IoT applications.

Table 1. Power use in various modes.

Logging		Streaming		Idle		
500Hz	100Hz	500Hz	100Hz	No conn.	BT conn.	Off
98mW	94mW	200mW	184mW	18mW	92mW	70μW

Data logging uses an optimised FAT32. Log files are pre-allocated contiguously on the SD card. This allows to employ SD card "pre-erase" and "multi block writes" commands which allow streaming writes of data, without having to regularly update the FAT entries and cluster link. Only when a file is closed is the FAT updated to reflect the size of the file. With this we achieved 1KHz ADC sample rate with jitter less than $\pm 30\mu S$ [5].

The motion sensor data is converted into orientation quaternions using a variation of Madgwick's algorithm [3], where the corrective step using the accelerometer and magnetometer is carried out at a fixed 12.5Hz. This allows to keep the computation time below 1100μS and is instrumental to achieve 500Hz motion sensing. We did not observe adverse effects thanks to the low noise of the gyroscope.

Timekeeping is obtained from a combination of an internal AVR timer and the RTC. The AVR timer provides a time resolution of 1ms. A 1Hz RTC signal is used to regularly reset the AVR timer. This ensures that the timekeeping error is bound by the RTC timekeeping accuracy.

4 Characterisation

We minimised CPU power consumption by sleeping the processor when busy-looping. In idle mode (i.e. waiting for commands), the dominant power contribution is the Bluetooth radio, which we minimised by modifying the inquiry and page scan window and duty cycling. This decreased idle power by 19mW at the expense of slightly longer discovery and connection time. In hardware off mode, the only components directly powered by the battery are the coulomb counter, the RTC and the power-up logic. The type of SD card used has a significant influence on power use during logging. Table 1 shows power use with a 32GB Samsung EVO+ SD card; using a 32GB SanDisk Extreme instead increased power use by 40mW.

5 Conclusion

BlueSense offers a better tradeoff and versatility for wearable sensing applications compared to many other platforms. It is smaller at 30x30mm than commercial solutions by Xsens (47x30mm for the wireless MTw), Shimmer (51x34mm for the Shimmer3 IMU) and x-io technologies (42x33mm for the x-IMU) and it offers higher sample rate (500Hz) than the XSens MTw (120Hz) and many other platforms [6], inluding highly miniaturised ones [1]. It is extensible, as is the x-IMU. True hardware off also allows usage in IoT applications. The bill of material is below £80 per unit (excluding assembly) in batches of 30.

An AVR processor was used to reduce development time by exploiting our large existing code base. The firmware development time was nevertheless significantly underestimated due to the highly specific needs of this platform requiring a large number of new software modules. A lesson learned for embedded systems development is that a more modern microcontroller could have been used (e.g. an ARM Cortex-M) while incurring only a very limited increase in development time. The platform will be open-hardware[1].

6 Acknowledgement

Part supported by EPSRC grant EP/N007816/1.

7 References

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