Smart Sensor Engineering:
A Case Study Based on Accelerometer Data

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Overview

This case study has been designed to evaluate how quickly and effectively smart sensing processes [1,2] can be configured, based on accelerometer data. This analysis is the latest among several that have been completed recently, based on a general smart sensing module that has been developed by the members of the Brainlike, Inc., smart sensing team [6-12]. Prior analyses and reports have been based on sensor data ranging from commercial electricity meters to side scan sonar on undersea, unmanned vehicles [6, 12-20]. This report, like those that came before it, shows that automated sensor processing modules, along with streamlined data analysis procedures based on them, can indeed accelerate smart sensor delivery. In this case, a model has been identified, after about a week of analysis, that can quickly be deployed using a closely related, general purpose processor. Alternative analyses would have taken much longer, and developing specialized processes that could implement them would have taken longer still.

The case study describes an analysis of noisy and marginally reliable accelerometer data. Marginal sensor performance is typical in an emerging field where engineering and affordability constraints limit sensor precision. In this case, the accelerometers being considered for deployment must be very small, they must operate with very low power, and they must be affordable. As a result, their measured values cannot be used to identify accelerometer states simply. If they did measure acceleration magnitude perfectly, their output values could determine both their location and velocity exactly. In practice, measured accelerometer values are typically greater than zero and highly variable, even when they were not moving at all. As a result, substantial data analysis must be performed, robust processes must be developed, and the smart sensing approach should be considered accordingly, as shown in the remainder of this report.

Results

Data were gathered to evaluate the extent to which a simple accelerometer, which was sufficiently small and potentially affordable for cell phone installation, could adequately determine whether or not the cell phone was moving or stopped, when it was attached to a moving vehicle. The dataset consisted of accelerometer and ground truth measurements, taken while the van was moving on a freeway without stopping, as well as moving in a city while making several stops at traffic intersections, over a period of about an hour. Accelerometer measurements were recorded 100 times per second. Meanwhile, ground truth measurements were recorded every second. Accelerometer measurements included acceleration as well as turning rate, along X, Y, and Z relative coordinates. Ground truth measurements included GPS-based latitude, longitude, and elevation measurements, along with velocity, relative acceleration and turning rate measurements from larger, more precise accelerometers.

Analysis of ground truth and accelerometer measurements showed that the ground truth velocity measurements were sufficiently accurate to determine whether or not the van was moving, within one second of periods when the van was stopped. These measurements were used for further analysis and evaluation of various smart sensing alternatives for the accelerometer data. Further analysis of the ground truth acceleration data, along with preliminary comparisons with the accelerometer data, showed that (a) ground truth accelerations were much more accurate than their accelerometer counterparts, (b) acceleration magnitudes based on the accelerometer measurements were often nowhere near zero when the van was stopped, and (c) even ground truth acceleration magnitudes were not highly correlated with each other.

start time (sec)	ground truth interval duration (seconds)	Brainlike hit prediction duration (seconds)	result hit (H), miss (M), or false alarm (F)	Comments:
515988	15	14	H	The missed second came at one end of the interval.
516064	10	10	H	Perfect coverage.
516121	18	17	H	The missed second came at one end of the interval.
516245	2	1	H	The missed second came at one end of the interval.
516357	16	14	H	Both missed seconds came at ends of the interval.
516423	23	22	H	The missed second came at one end of the interval.
516489	23	21	H	Both missed seconds came at ends of the interval.
516596	9	7	H	Both missed seconds came at ends of the interval.
516611	47	44	H	The missed second came at one end of the interval.
516658	0	2	F	This happened immediately after the previous stop.
516682	8	6	H	Both missed seconds came at ends of the interval.
516798	21	19	H	Both missed seconds came at ends of the interval.
516944	3	0	M	This stop lasted only three seconds
516977	9	8	H	The missed second came at one end of the interval.

Figure 1. Interval Performance Summary.

As a result, a variety of smart sensing alternatives were considered, including all five that were listed in the previous section. A composite feature, which measured how much each set of 100 measured values in a second varied, was the best single classifier of moving versus stopped states. Adding a feature that measured acceleration magnitude during movement improved results. Adding a rule that required each second to be classified as moving if the second before and after it was classified as stopped based on the first two features improved results further.

The resulting smart sensing model was developed, based on data from the period when the van made half of its stops. The model was then evaluated for the period when the van made its remaining stops. Results at the event level (see Figure 1) showed that all stopping periods, ranging from two seconds to 47 seconds, were correctly identified, while only one stopping period, lasting three seconds, was missed. One moving period, lasting two seconds and coming within five seconds of a stopped period, was incorrectly classified as a stop.

Results at the second level (see Figure 2) showed that during the 1,999 seconds that were analyzed, actual stops occurred during 183 seconds and all but 21 were correctly classified as stopped by the smart sensing process. Among the 1,795 remaining seconds when the van was actually moving, all but three were properly classified as such.

The smart sensing analysis process required less than a person-week of effort to identify the model that produced the Figure 1 and 2 results. The resulting model could be immediately deployed on a Brainlike Processor™ module. The module could reside on a digital signal processing chip or a field programmable gating array, suitable for simple integration on a cell phone processor. The cell phone processor could send the accelerometer data to the smart sensing module in real time, receive stopped versus moving indicators in real time, and control cell phone operations, including telemetry in real time, accordingly. The smart sensor could also be configured to thwart adverse affects and control for changing accelerometer, clutter, and environmental conditions automatically.

COUNTS:

	actual stopped	actual moving	
predicted stopped:	183	3	186
predicted moving:	21	1792	1813
	204	1795	1999

PERCENTAGES:

89.71%	0.17%
10.29%	99.83%

Figure 2. Interval Performance Summary.

Conclusions

A careful analysis of the accelerometer dataset for this study by signal processing experts could have been performed. The resulting model could have classified intervals as stopped or moving, with precision as high as or even higher than the precision from this study. But that's not the point. The reported analysis quickly produced accurate results, in a form that could be quickly deployed on a smart sensor module. The smart sensor would operate in real time, it would be proven, it would be dependable, <u>and it would be robust against changing or even unforeseen background conditions</u>. The overall conclusion is that sensor system engineers should consider using smart sensing modules and analysis tools, in order to develop and deploy more robust sensing systems, more quickly, and at lower cost.

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