An Energy Efficient Localization Strategy for Outdoor Objects based on Intelligent Light-Intensity Sampling

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Abstract. A simple and low cost strategy for implementing pervasive objects that identify and track their own geographical location is proposed. The strategy, which is not reliant on any GIS infrastructure such as GPS, is realized using an electronic artifact with a built in clock, a light sensor, or low-cost digital camera, persistent storage such as flash and sufficient computational circuitry to make elementary trigonometric computations. The object monitors the lighting conditions and thereby detects and tracks the sunrise and sunset times. By the means of a simple celestial model an estimate of the geographical position of the object can be made. An intelligent light sampling method is proposed allowing the object to sleep most of the time and hence save battery power. The strategy is energy efficient and the speed of convergence can be adjusted as a function of the energy consumed. Objects employing the method can therefore operate for long times without recharging their batteries. The strategy has applications in mobile sensor networks where nodes need to log geographical information, sensing equipment such as floating buoyancies, or pervasive technologies in need of geo-spatial information such as digital cameras, mobile devices, etc.

Keywords: intelligent objects, geo-location, object tracking

1 Introduction

Geographical information is an important attribute of modern information systems, especially within the field of mobile, pervasive and ubiquitous computing systems [7]. For instance, geo-tagging is particularly useful for image tagging allowing more convenient organization and retrieval [3] of images. Current solutions usually rely on GPS which provides excellent accuracy. However, GPS devices are expensive, consume much electrical power and take a long time to lock onto overhead satellites. The most worrying aspect about the GPS technology is that this infrastructure is reaching the end of its lifetime and there is yet no realistic replacement available [5]. Several strategies that omit GPS technology have been proposed. For instance in sensor networks one may find the location of a sensor by triangulating according to range using the location of other neighboring anchor sensor whose location is known [18]. In the field of image recognition landmark recognition has been used to determine the location of the observer by identifying known landmarks [19]. Clearly, this is an ambitious strategy that both depends on powerful image processing algorithms and extensive landmark databases. Another branch of research is inspired by traditional navigation according to the celestial bodies including the sun, stars and the moon, and also the detection of time [6, 16]. Of these, geographical locations have been estimated based on direct sun observations, that is, observation of the sun elevation over the horizon by the means of a camera [4, 17]. Problems with these strategies are that they either require a wide angle lens or very low sun elevations. Instead, it has been proposed to measure the sun elevation indirectly using shadows [11, 14]. One problem with sun observations is that it will only work on sunny days. To combat this it has been proposed to measure the sun elevation indirectly using the overall light intensity of images as even on cloudy days the light intensity will vary with the hour of the day [12, 15]. Related research has the access to regular image sequences acquired by webcams and these can be used to detect the relative location of webcams [8, 9] or absolutely by identifying sunrise and sunsets [13].

2 Method

The method proposed herein can be reformulated as the problem of identifying and tracking the sunrise and sunset times. The strategy therefore has two major stages, namely initialization involving the identification of sunset and sunrise times and tracking involving detecting object motions by observing changes in the sunset and sunrise times. This paper first outlines hardware requirements. Next, the employed celestial model is presented. Finally, the initialization and tracking procedures are described.

2.1 Hardware requirements

The method proposed herein is based on electronic objects with a built in clock which maintains a relatively accurate account of time and date. Digital clocks are built into most electronic hardware nowadays and can run for many years on one single battery with limited drift. It is therefore assumed that at any time the object can enquire the current time t and date d. It is assumed that the time is set to Universal Time (UTC) which makes the calculations presented herein simple and is represented in decimal form in the range from 0 to 24. Issues such as daylight saving time are thus avoided. Next, the date d is represented as the day of the year, where January 1st is day 1, etc. In this strategy the year information is not used.

Next, the strategy requires that the electronic object has some form of light sensor that is capable of measuring the lighting condition e. This can for instance be a simple and low cost exposure value meter such as those built into most low-cost digital cameras [1, 2, 10] or it could be a low cost camera (CCD-chip). In the cases of exposure values (EV) then e is a real value between 0 to approximately 20. If a camera is used a simple representation of exposure can be obtained simply using:

$$e = \frac{1}{X \cdot Y} \sum_{x=1}^{X} \sum_{y=1}^{Y} I_{x,y} \tag{1}$$

Where $I_{x,y}$ is the pixel intensity for the pixel located at x, y in the image and X and Y are the width and height of the image, respectively. To reduce computation a small subset of these points can be sampled throughout the image using some two dimensional sampling pattern.

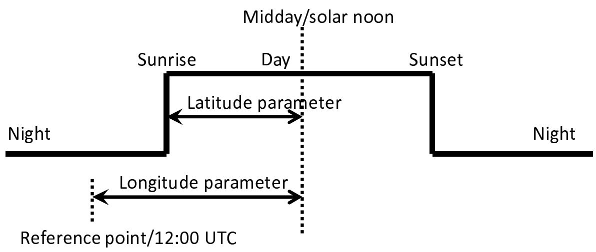

Fig. 1. Daylight parameters influenced by latitude and longitude.

2.2 Celestial model

The method described herein can be reduced to the problem of identifying and tracking the sunset and sunrise times. Given an accurate measurement of the sunrise time $t_{sunrise}$ and sunset time t_{sunset}, the solar noon t_{midday} is simply:

$$t_{midday} = \frac{t_{sunset} - t_{sunrise}}{2} \tag{2}$$

Note that it is assumed that the sunrise occurs before the sunset in the representation of time. If the sunset occurs "before" the sunrise then the computations wrap around so that they fit within the range of 0 to 24.

Next, the angular sunset a_{sunset} can be computed as follows:

$$a_{sunset} = \frac{\pi}{12}(t_{sunset} - t_{midday}) \tag{3}$$

Note that the sign should be inverted if the sunrise occurs after the sunset within the 24 hour UTC time window. Then, the latitude φ of the objects location can be found by numerically solving for latitude using the following equation:

$$\cos(a_{sunset}) = \frac{\sin(-0.83) - \sin(\varphi) \cdot \sin(\delta)}{\cos(\varphi) \cdot \cos(\delta)} \tag{4}$$

Where δ is the declination of the sun and can be approximated by

$$\delta = -0.4092797\cos\left(\frac{2\pi}{365}(d+10)\right) \quad (5)$$

Finally, the longitude of the object is simply found using:

$$\lambda = 2\pi\frac{12 - t_{midday}}{24} \quad (6)$$

These parameters are illustrated in Fig. 1.

2.3 Initialization

2.3.1 Brute force

Initialization involves locating the time of the sunrise and sunset for an object when first switched on. The geographic location identified during the initialization is later used during tracking. Given a sufficient supply of electric power, for instance if the object has a steady power supply the initialization can be simply be performed using brute force by continuously sampling the lighting condition. If the light sensor is sampled at r samples per second, then this is the same as M samples for each 24 hour cycle, given by:

$$M = 24 \times 60 \times 60 \times r \quad (7)$$

The accuracy of the measurements will therefore be in the range of:

$$a = \frac{360}{M} \quad (8)$$

It will take maximum 24 hours to identify the location and the effort involved is defined by $E=Mp$ where p is the energy consumed to perform each sample and E is the total energy. This is the optimal solution in terms of speed and accuracy. However, for a power constrained device the strategy is unrealistic as a very simple device could run out of power after just a few hours or sooner. In the following a series of more energy efficient strategies will be explored.

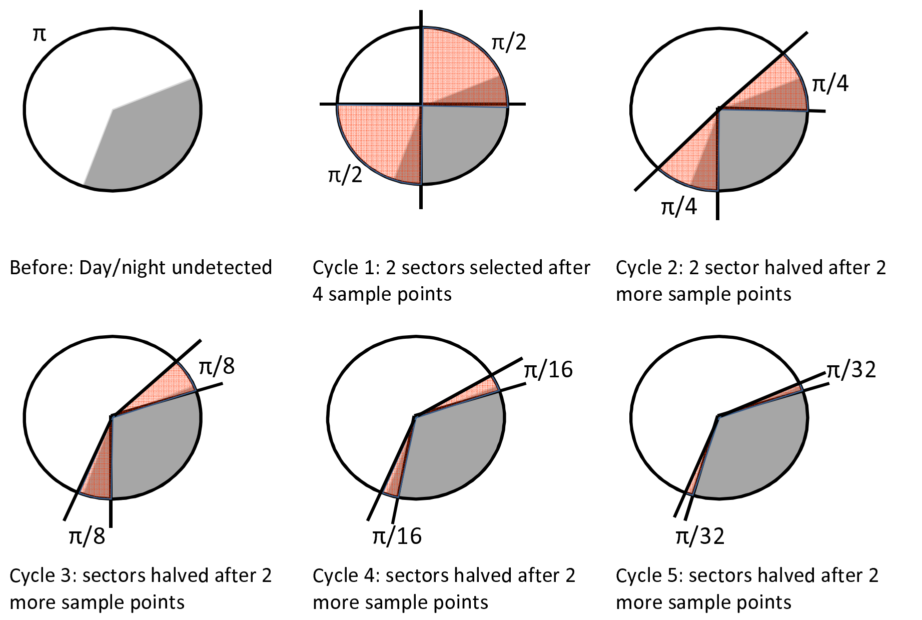

Fig. 2. Binary subdivision initialization

2.3.2 Binary subdivision

The strategy presented herein is based on iterative subdivision. Each 24 hour cycle defines one round, or one iteration, and the brute force method is simply based on performing the initialization in one round. Imagine instead that at each round only one sample is taken at a strategic location and that a pattern of the whereabouts of the sunrise an sunsets is established over time. In the first round two samples are taken, namely at 0 UTC and 12 UTC. This allows us to determine with 180 degree accuracy when it is night and when it is day. Next in the second round two more samples are taken at 6 UTC and 18 UTC. Then, one will be able to determine the location of the sunrise and sunset down to a sector of 90 degrees. Then for the third round the two sectors where the sunrise and sunset are located is further subdivided in two equal halves by sampling the midpoint. This procedure continues until the desired accuracy is acquired. In general, at round n the sunset and sunrise times are determined with an accuracy a of

$$a = \frac{360}{2^n} \tag{9}$$

Alternatively, the number of steps, that is, 24 hour cycles, it takes to achieve an accuracy of *a* with this strategy is:

$$n = \frac{\ln\left(\frac{360}{a}\right)}{\ln(2)} \tag{10}$$

The energy consumed is thus:

$$E = 2np \tag{11}$$

where p represents one unit of consumed power sampling the light intensity.

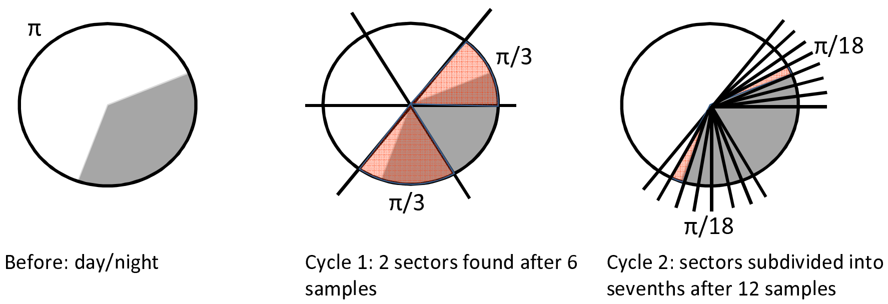

Fig. 3. N-way subdivision initialization

2.3.3 N-way subdivision

A problem with binary subdivision is that it can take quite a few days to get a good lock on the sunrise and sunset times. In the mean time the object might have moved or the changes in the season may have significantly affected the sunrise and sunset times because of changes in sun declination. In other situations it may be desirable to obtain a more instant geographical estimate of the location by investing more power. For this purpose an *N*-ary subdivision scheme may be employed. With the *N*-way subdivision scheme the 24 hour cycle is first split into four 90 degree sectors. Then, the two sectors where the sunrise and sunset may be present are further subdivided *N*-ways and so forth. After n steps the acquired accuracy is therefore

$$a = \begin{cases} \frac{360}{4N^{n-1}} & \text{if } N \leq 4 \\ \frac{360}{N^n} & \text{if } N > 4 \end{cases} \tag{12}$$

Alternatively, to achieve an accuracy of a with N subdivisions n steps are needed, namely:

$$n = \begin{cases} \dfrac{\ln\left(\dfrac{360}{4a}\right)}{\ln N} + 1 & \text{if } N \le 4 \\ \dfrac{\ln\left(\dfrac{360}{a}\right)}{\ln N} & \text{if } N > 4 \end{cases} \tag{13}$$

And, the energy consumed is

$$E = \begin{cases} 4p + 2N(n-1)p & \text{if } N \le 4 \\ 2Nnp & \text{if } N > 4 \end{cases} \tag{14}$$

2.3.4 Analysis

Table 1 lists the characteristics of the three initialization strategies for various accuracy requirements. According to these estimates an accuracy of 0.1 degrees is realistic as this relies on the sunset and sunrise to be detected with an accuracy of just below half a minute. For higher accuracies it may not be realistic under general conditions to obtain a sufficient accurate lighting condition measurement. Assuming that an accuracy of 0.1 degrees is the target, namely 1.1 km, the table reveals that with the binary methods this will take 12 days, and just 2 days with a 100-way strategy. However, the more rapid determination requires next to 2,000 % more energy than the binary method. A good balance is struck with the 4-way method which finds the location with the desired accuracy in half the time, namely in 6 days with just twice as much energy consumed, or in just 4 days with 4 times as much energy consumed. In comparison the brute force method would need to take 3,600 samples during one cycle to achieve an accuracy of 0.1 degrees and hence consume 3,600 units of energy which is nearly 10 times that of the 100-way strategy. However, the location would then be found in 24 hours in the worst case.

Table 1. Theoretical accuracy, convergence time, and energy consumption parameters for intelligent intensity light sampling.

		binray		3-way		4-way	
Acc. (deg)	Acc. (time)	cycles	E	cycles	E	cycles	E
10	40 min	6	12	3	16	3	20
1	4 min	9	18	6	34	5	36
0,1	24 sec	12	24	8	46	6	44
0,01	2.4 sec	16	32	10	58	8	60
0,001	0.24 sec	19	38	12	70	10	76
0,0001	0.024 sec	22	44	14	82	11	84

		5-way		10-way		100-way	
Acc. (deg)	Acc. (time)	cycles	E	cycles	E	cycles	E
10	40 min	3	30	2	40	1	200
1	4 min	4	40	3	60	2	400
0,1	24 sec	6	60	4	80	2	400
0,01	2.4 sec	7	70	5	100	3	600
0,001	0.24 sec	8	80	6	120	3	600
0,0001	0.024 sec	10	100	7	140	4	800

2.4 Tracking

Once the geographical location of the object is detected one may wish to track the new position of the object if the object has moved. If the object is stationary then no tracking is needed. The degree to which an object is moving will depend on the specific application. Therefore, a dynamic strategy is proposed herein that can be used to adjust the tracking according the needs of the application.

2.4.1 Object speed and distance travelled

First, one should define the maximum theoretical speed s of the object in meters per second. Given a maximum speed of s then the maximum possible distance in meters that can be travelled during one 24 hour cycle is $D = 24 \times 60 \times 60 \times s$. The potential distance travelled in a single 24 hour cycle is of particular interest as sunrise and sunset measurements can only be taken once each 24 hours. As there is 1,852 meters in one nautical mile, that is, one arc minute, the total distance in degrees W is therefore:

$$W = \frac{24 \times 60 \times s}{1852} \quad \textbf{(15)}$$

For example, imagine that the object is mounted on a road vehicle such as a car with a maximum speed of 100 km/hour, then, the maximum theoretical distance travelled in degrees during a 24 hour cycle is 21.5 degrees. However, the practical distance is likely to be much smaller if the vehicle is driven by a single person as a person is unable to drive for 24 hours. A more realistic number is in light of this is 7 degrees. Moreover, the driver may not drive in a straight line and will also be unable to maintain a speed of 100 km/hour and the net distance is therefore yet smaller.

Still, a maximum threshold of W may be used as a limit on the sunrise and sunset times if converted to hour angle t_W.

$$t_w = \frac{24}{360} W \tag{16}$$

2.4.2 Seasonal changes

The declination of the sun affects the sunset and sunrise times according to Eq. (4). These changes are quite large on a daily basis close to the solstices. Given the previous longitude and latitude and the sun declination angle for the current cycle revised sunrise and sunset times can be computed using Eq. (4).

2.4.3 Dynamic tracking

During each cycle a sample point is taken just before (pre-test) and after (post-test) the sunrise and the sunset times adjusted for seasonal changes due to the declination of the sun. These measurements are further separated a apart. Now, if say the second of the two tests fail, then this is an indication that the sunrise or sunset occur later and one therefore continues to sample points at regular interval separated by a until the test is true or, until the difference between the original test and the point is W. If the test is still false the next sample point is taken at a distance of W, then $2W$, $4W$, $8W$, etc, until the test is true. Using this strategy the new position can be detected during the same cycle. The pre-test and post-test mechanism is stated in Table 2.

Table 2. Interpretation of pre-test and post-test results.

Pre-test	Post-test	Type	Interpretation	Action
Day	Night	Sunset	Stationary	
Day	Day	Sunset	Later sunset	Sample more points
Night		Sunset	Earlier sunset	Sample earlier next cycle
Night	Day	Sunrise	Stationary	
Night	Night	Sunrise	Later sunrise	Sample more points
Day		Sunrise	Earlier sunrise	Sample earlier next cycle

If the first of the two tests fail, then this is an indication that the sunrise or sunset has already occurred. In this situation the new position needs to be detected during the next cycle. The strategy is therefore to take a sample at $-W$ before the failed test and at regular intervals separated by a until the test is true. If one reaches the same point in time as the previous cycle then the new sunrise or sunset has occurred before $-W$, and yet another cycle is needed. In the third cycle a sample is taken at $-W$. If this test is true then regular samples at separated by a are taken. If the test is false, another test at $-2W$ is taken during the next cycle, and so forth.

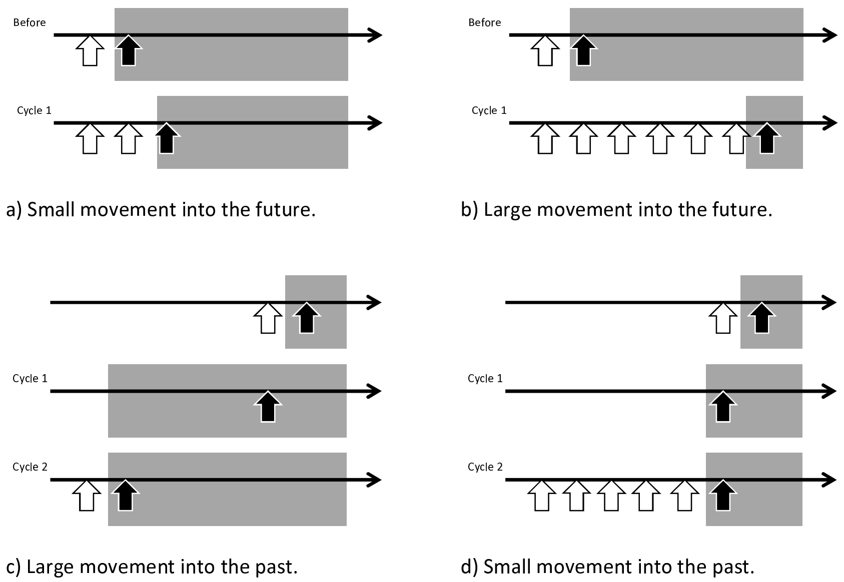

Fig. 4. Tracking sunset changes. White arrows signify tests that yields daylight and black arrows denote tests that return night. The gray box mark night. Time is represented left to right.

Fig. 4 illustrates the tracking procedure. Fig. 4 a) shows an example where the sunset is slightly delayed. This is detected in the 1st cycle as the second test yields daylight instead of night. Therefore, another sample is taken one time step later which then yields night and the new sunset time is detected. Fig. 4 b) shows a larger sunset change. Here, the second test again yields day and the test is repeated at regular intervals until the test returns night. In this example, another five tests are needed to successfully determine the magnitude of the change. Fig. 4 c) shows a large change into the past, that is, the sunset occurs much earlier than before. During the first cycle the first test returns night and the algorithm therefore knows that the sunset has already occurred. During the next cycle the tests start earlier according to the maximum threshold W, in this case six steps earlier. The first test yields day and the second test yields night and hence the new sunset time is successfully detected. In this instance the new sunset is found with very few additional tests, but it takes one more cycle to determine the new location compared to when the sunset is postponed. Finally, Fig. 4 d) shows a small change in sunset time towards an earlier time. Also, here the first test returns night and the algorithm know that the sunset has occurred earlier. During the subsequent cycle the testing begins six time units earlier and six tests are needed until the sunset is detected. In this instance slightly more effort is needed, but the change is successfully detected with the desired accuracy.

Table 3. Linguistic interpretations of changes in day length and solar noon. Here t_0 and t_1 denote the time of the solar noon in UTC for the previous and current cycle, respectively, and δt_0 and δt_1 denote the length of day at the previous and current cycle, respectively. Combinations are possible, for example north-east, south-west, etc.

solar noon	day length	season	movement
$t_1 = t_0$	$\delta t_1 = \delta t_0$		no movement
$t_1 > t_0$			west
$t_1 < t_0$			east
	$\delta t_1 > \delta t_0$	winter	south
	$\delta t_1 > \delta t_0$	summer	north
	$\delta t_1 < \delta t_0$	winter	north
	$\delta t_1 < \delta t_0$	summer	south

2.4.4 Analysis

The advantage of the outlined tracking procedure is that only 4 samples need to be taken every 24 hours when the object is not moving to confirm that the object is stationary. However, the strategy is able to instantly track small movements in either one or two cycles with limited number of additional samples. Next, the strategy is also able to track larger movements, but with lesser accuracy and in some cases it needs more cycles to detect the changes.

Movements towards the west can be detected during the same cycle irrespective of the magnitude, while movements towards the east will be detected during the next cycle if they are small or after a few more cycles if the movement is larger. A motion towards a pole during its hemispheres winter season will be detectable in the same cycle while a motion towards a pole during its hemispheres summer season is detected during the next cycle or later, depending on the magnitude of the movement. This is illustrated in Table 3.

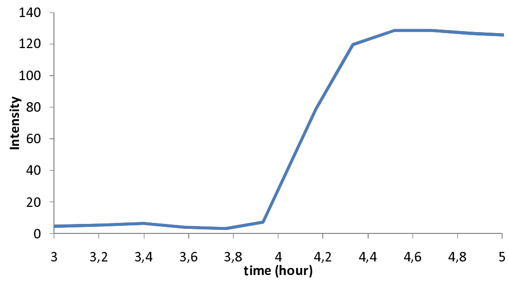

Fig. 5. Gradual increase in intensity towards sunset

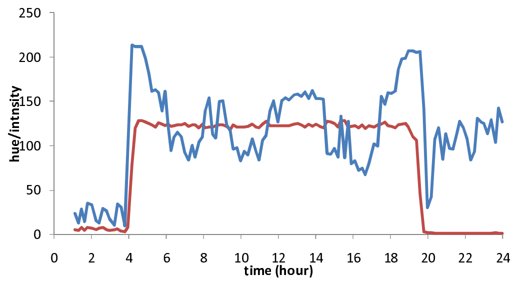

Fig. 6. Sudden hue changes predict sunrises and sunsets

2.4.5 Enhancements

Several theoretical enhancements are possible. Sunrises can be predicted if early measurements are taken. This is because the light intensity increases gradually over some time interval before one passes the threshold of 85% of full daylight intensity which is used in this study. If a light intensity measurement is taken that is above the night baseline value but yet below the threshold then this is a sign that a sunrise is approaching soon and the sample rate can be dynamically increased. This is illustrated by Fig. 5 which shows an authentic intensity plot obtained using a webcam. Clearly the intensity rises for about 20 minutes before the sun breaks.

However, it may be more difficult to get a pre warning of a sunset in this way as this will suddenly drop below the threshold value. One way to overcome this is to observe additional features. If the light sensor is capable of capturing color spectrum information then additional information can be exploited to better predict sunrises and sunsets. For instance, the CCD sensors in digital cameras are capable of detecting color as well as intensity. This is because sunsets and sunrises often are characterized by large changes in overall changes in hues which affect entire scenes. Such changes in hue occur prior to sunsets and thus a detection in hue change can be used to predict an upcoming sunset. This is illustrated in Fig. 6 which is an authentic 24 hour plot obtained using a webcam. The steady line shows the overall image intensity and the other line illustrates overall image hue. Clearly, the hue is changing dramatically just before the sunrise and sunset. In fact, these can be seen as the two peaks in the hue plot. However, the exploitation of such features is the topic of future research.

3 Limitations

There are several challenges associated with the proposed strategy. Firstly, the strategy assumes a relatively steady view of its surroundings. If the object is constantly moving about in various directions the light intensity may be affected and consequently lead to erroneous sunrise and sunset detections. Moreover, other effects such as weather conditions may impact the results. Although the strategy works on both cloudy and sunny days, days with extremely heavy blankets of clouds may introduce erroneous readings.

Another source of error could be the accuracy of the clock. It is natural for clocks to drift. Modern electric clocks are often driven by quartz crystals whose frequency varies with temperature. Objects submerged in environments with extreme temperatures, such as sensors in arctic climates, may be affected if equipped with low cost clock hardware.

4 Conclusions

A strategy for building low-cost and GPS-independent geo-awareness into ubiquitous objects was presented. The strategy is based on maintaining accurate time and irregularly sampling the outdoor lighting conditions, thereby detecting the sunrise and sunset times. The sunrise and sunset times are used with a celestial model to derive the estimated latitude and longitude of the object, and under optimal condition the method holds potential of achieving an accuracy of 0.1 degrees or about 11.1 km accuracy. The strategy is energy efficient and its energy consumption can be adjusted dynamically according to desired responsiveness. For objects that are very mobile, that is, travel great distances at high speeds more energy is needed to quickly detect the changes. However, for objects with very little motion a less aggressive sampling strategy can be employed.

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