Cost-efficient Localisation System for Agricultural Use Cases

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Keywords: Agriculture, Low-cost Localisation, Trilateration Simulation.

Abstract: Connected agricultural applications often depend on exact localisation solutions. Often the term "precision agriculture" implies a technology that identifies the location of the livestock, crop, field of agricultural machinery with more or less of precision. While precision requirements vary, the localisation often has to be quite precise like sub-meter or even decimeter precision. Dual-band GPS solutions are able to satisfy these high-precision requirements but these equipments are quite costly and their purchase is often regulated. This paper presents two agricultural use cases and the combination of low-cost GPS and short-range localisation systems that are able to satisfy high-precision requirements for fraction of the costs of dual-band GPS.

1 INTRODUCTION

Connected sensor applications in the agriculture domain often require precise localisation functionality. The state-of-the art solution is high-precision dual-frequency GPS receiver with Real-Time Kinematic (RTK) support. Typically these receivers cost 3-4000 USDs and have strict control of purchase which makes them suitable for a costly agricultural machine like a combine-harvester but are prohibitively expensive for localising less valuable moving objects. Precise localisation requirements have arisen in two separate projects run by the institutions collaborating in the research described in this paper. At ESEO, the task is to localise dairy cows with a precision of less than 1 meter. At Széchenyi University our task was to mobilize the agricultural camera sensor (Paller and Élő, 2016) by mounting it onto a robot vehicle that traverses a predetermined trajectory. For this use case, precise localisation is needed to keep the robot on the tracks (typically dirt roads) used by agricultural machines. We targeted the precision requirement of better than 1 meter in this case too. In both cases, the value of the objects to be tracked does not justify expensive GPS receivers that are also hard to protect against theft on the field.

Even though the requirements seem to be similar, they are not the same. The robot localisation task may allow a limited number of fixed stations while for the cow localisation, the use of such fixed stations is discouraged. The robot's movement is under our control, e.g. it is possible to stop the robot to allow for more precise localisation. For the cows, such "stopping" is not possible.

The paper shall be organised as follows.

- Section 2 presents our findings with regards to the precision of low-cost standalone and differential GPS solutions.
- Section 3 evaluates a low-cost differential solution.
- Section 4 presents behavioural analysis of dairy cows based on publicly available measurement data that supports our proposal for a localisation solution using RTK GPS and short-range localization technologies.
- Section 5 presents our proposal for distance-based short-range localisation technique.
- Section 6 presents our proposal for an angle-based short-range localisation technique.

2 EVALUATION OF LOW-COST STANDALONE AND DIFFERENTIAL GPS

GPS measurements are subject to satellite and receiver clock errors, ionosphere and troposphere propagation delays, multipath and random noise errors. The most interesting factor of standalone (non-differential) GPS receivers is the ionospheric delay.

Paller G., Aubin S., ÃĽlÅŚ G. and Camp O.
Cost-efficient Localisation System for Agricultural Use Cases.
DOI: 10.5220/0006137501420149
In *Proceedings of the 6th International Conference on Sensor Networks (SENSORNETS 2017)*, pages 142-149
ISBN: 421065/17

The electromagnetic property of the ionosphere influences the electromagnetic signals' propagation speed, including that of GPS signals. As the signal propagation speed is used in the pseudorange calculation (the satellite's distance from the receiver deduced from the signal delay between the satellite and the receiver), changes in the real propagation speed introduce errors into pseudorange calculations. This error ranges from 1 meter to up to 50 meters in case of satellites with low elevation and even higher in case of increased solar activity.

Ionospheric delay is complicated from the error correction point of view because it introduces systematic (non-random) location measurement error. Eventually the mean value of this error is close to zero but that needs very long observation period, in the range of several hours (Langley, 1991). Dual-frequency GPS receivers can filter out this error but these receivers are very costly. Space-Based Augmentation Systems (SBAS) is a differential GPS technology that transfers corrections over satellites that are distinct from GPS satellites, still transmit data on GPS frequencies. SBAS signals are often problematic to receive on ground level. We made measurements with SBAS-equipped GPS receivers to figure out, what precision can be achieved with this technology in our use cases. The SBAS receiver was MediaTek 3339, equipped with ceramic patch antenna or external active antenna. As reference, Ashtech Z-Xtreme high-precision dual-band receiver was used in static survey (non-differential) mode. The measurements were made in the Angers area, France. We also made measurements at a geodetic reference site (Ecouflant I) whose coordinates have been established with high precision by the National Institute of Geographic and Forestry Information (IGN) of France.

Figure 1 shows the results of a typical measurement at the reference site. The origo of the graph is the IGN reference coordinate for the site, deviation from the origo means measurement error. MTK3339_2 was not able to lock on the SBAS signal (even though the other two modules in its vicinity were eventually able to receive SBAS corrections), this fact is reflected in its much less precise measurements than MTK3339_1 and MTK3339_3. The two modules that did lock on SBAS produced much less precise locations than the 1 meter error required. Even the advanced Ashtech reference receiver had a maximum error that was larger than 1 meter.

The maximum error relative to the reference point measured with the MTK3339 was in the 2.22-11.51 meters range. All the measurements were made in an environment that models agricultural conditions: mostly flat area with minor depressions, low vegetation with occassional trees. The reference coordinates were either taken from the Ashtech receiver (when the measurement was not performed at the geodetic reference point) or were the coordinates specified by IGN for the reference point. The measurement sessions lasted 10 minutes, measured from the moment when all the 3 SBAS receivers locked on the SBAS signal. This could take quite a long time depending on the location and time of the day, it was quite common that 10-15 minutes needed from the first GPS location fix to the first SBAS fix and there were measurements when one module could not even obtain SBAS fix, in spite of the fact that the SBAS receivers were placed very near to each other (3 centimeters). When the SBAS signal was not acquired, the maximum error was 30.89 meters. Our conclusion based on the field measurements is that low-cost GPS receivers even with SBAS differential corrections are not able to satisfy our requirement of 1 meter accuracy. In addition, SBAS signal cannot be reliably acquired on ground level.

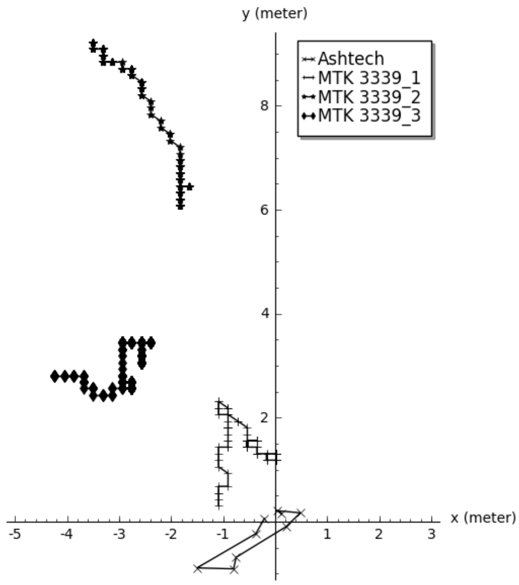

Figure 1: Results of one measurement at Ecouflant I site.

3 EVALUATION OF LOW-COST DIFFERENTIAL GPS

Our measurements presented in section 2 convinced us that a low-cost GPS receiver supporting only the L1 band is only able to support our accuracy requirements if it is used in differential mode. The goGPS software (Herrera et al., 2016) was created to support exactly these kinds of receivers with dif-

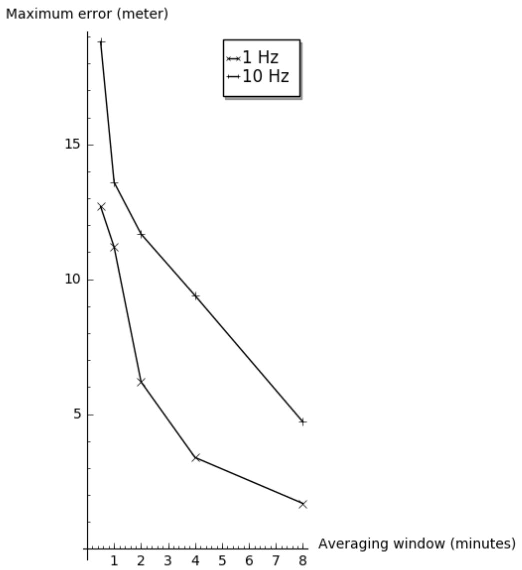

Figure 2: Maximum position error as a function of sampling frequency and averaging time.

ferential support. Readers interested in the details of goGPS should consult the cited references, only a brief overview is presented here.

In order to enhance the baseline accuracy of low-cost receivers, goGPS relies on raw observation data (pseudorange, carrier phase) from the GPS receiver, provided by the u-blox LEA-6T receiver in our case. We used goGPS in off-line mode when the rover and the master are not connected during the measurements. It is possible to set up the system with two low-cost receivers (one in master role located at a well-known coordinate and one in rover role) or with one professional reference station in master role (we used IGN's NGER reference station which is about 10 km from the location where the measurements were made) and a low-cost receiver in rover mode.

Double differencing in differential GPS mode eliminates efficiently the effect of ionospheric delay but other error terms like random noise, multipath effects and receiver clock errors still affect the locations calculated by the goGPS software. Figure 2 shows the maximum position error when the GPS receiver sampling frequency was 1 Hz and 10 Hz as a function of sliding averaging window length. The window length was between 0.5 min and 8 min. The figure demonstrates that the residual position error can be efficiently decreased with low-pass filtering but this affects the temporal sensitivity of the system which cannot be compensated by increasing the receiver's sampling frequency.

The effect of high-quality reference station master vs. using a low-cost receiver as master was also evaluated. High-quality reference station decreases the noise of at least the master receiver. On the other hand, the IGN reference station had a sampling period of 30 seconds. The goGPS software assumes a 1:1 relationship between rover and master samples, discarding rover samples if there is no corresponding master sample. The outcome is a significant reduction of effective sampling frequency which reduces the averaging window size to achieve the same temporal sensitivity. We evaluated the effect in two measurements and we found that the maximum error with low-cost master station was 1.3 meters while the maximum error with IGN master was 3.31 meters. While this measurement cannot be considered extensive, it indicates that high-quality master may improve the accuracy only if its sampling frequency is comparable with that of the rover.

We conclude that goGPS is indeed capable of producing location measurements using data from low-cost receivers if the target is stationary for at least 8-10 minutes. In case of moving targets (in particular in case of targets moving unpredictably like the cows) its error quickly increases so that trajectory tracking becomes impossible.

4 BEHAVIOURAL ANALYSIS OF DAIRY COWS

In this section we analyse whether it is possible to measure cow location in spite of the restriction imposed by goGPS' deficiency in tracking moving targets. The other use case is simpler as we control the movement of the robot entirely so if there is a need of a precise location fix, we can stop the movement for the required period. Cows, however, move according to their will and if they do not stay stationary for long enough, the low-cost rover will not be able to acquire the target's accurate position even occasionally. This phase of the research was accomplished based on data sets acquired by earlier research projects. (Wietrzyk and Radenkovic, 2007) (from now called Nottingham measurement) tracked 6 dairy cows for 2 days using GPS collars. Based on our experiences about GPS accuracy (see section 2), we consider the target stationary if its location does not change more than 3 meters from the baseline position acquired when the assumed stationary period started for 10 minutes. (De Weerd et al., 2015) (from now called Weerd measurement) tracked 9 cows for 11 days and added human observations to high-frequency GPS data. Human observations attach 7 labels to high-frequency GPS data of which we considered 5 (“Drinking”,“Dry forage”,“Foraging”,“Standing”, “Grooming”) as stationary. If the animals stayed for at least 10 minutes

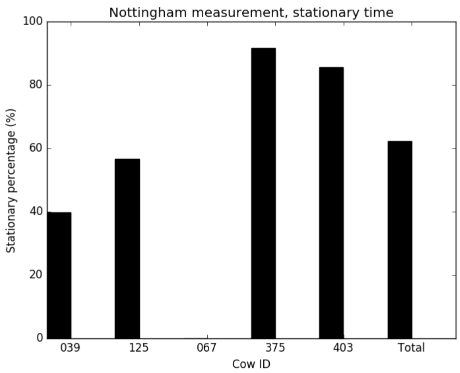

Figure 3: Stationary time per cow, Nottingham measurement.

in a stationary state, then the time spent in the state was added to the stationary time. The total stationary time was derived in this case entirely from human-observed labels. We processed only open-field (as opposed to forest) measurement in this paper.

Figure 3 presents the stationary time for the Nottingham measurement, by cow. One cow was found to be stationary all the time and its data has been eliminated from this chart. In general, the cows spend 40-90% of their time stationary even though the one with ID of "067" was constantly moving. Eventually on average the 5 cows were stationary for 62.3% of their time.

The Weerd measurement presented much more uniform picture. All the 9 cows were found to be stationary between 79.5 %-89.8 % of the time with an average of 80.9 %. We therefore concluded that even though the movement pattern of the animals depends on the particular cow, it can be assumed with high probability that at least some animals in the group stay stationary for the time period needed for an accurate GPS measurement. These animals can be used as reference points to locate the animals that were found to be moving with short-range distance or angle measurement methods.

5 DISTANCE-BASED SHORT-RANGE LOCALISATION

The problem of the distance-based short-range localisation is the following. We intend to localise a point with unknown position on a 2D map based on distance measured from reference points with well-known positions. We can then calculate the position of the unknown point with a trilateration algorithm (Cheung et al., 2006). We assume that the cows are equipped with an Ultra-Wideband (UWB) range measuring system and a GPS. There are competing UWB technologies on the market that we are still evaluating. UWB system is for the relative distance estimation among the animals and the GPS is for absolute positions. We have to understand how the errors of each system affect the unknown position's estimation error. Trilateration studies often omit the error to simplify the equations' resolution.

The first part of our simulation is a simple problem with N well-known fixed points. If we measure all the distances $r_{n\_wpt/u}$ between the well-known points with the following coordinate $[x_{n\_wpt}, y_{n\_wpt}]$ with $n\_wpt = 1, ..., N$ and the unknown point $[x_u, y_u]$, we can find the unique point, only if all the well-known points are not aligned. a system with simple circles equations give this results.

5.1 The Effect of Distance Measurement Error

In the first simulation we tried to find how an error on distance measurement could affect the reconstruction of the unknown point. The aim of this simulation is to verify if we can reconstruct the position of an unknown point and to determine what is the error of the unknown point estimation in the presence of distance measurement error. We have tried $N = \{4, 5, 6, 10, 20\}$. We chose the location of these well-known points according to real grazing situation. In (Dumont et al., 2005), the domestic herbivores used to graze in group. Few animals are alone. The selected plot is an area of maximum 300 meters $\times$ 300 meters. As example, this is the coordinate for 10 fixed points: $[0,0]$; $[0,5]$; $[-10,10]$; $[-10,-6]$; $[100,100]$; $[10,-8]$; $[70,-40]$; $[80,-45]$; $[75,-35]$; $[-5,90]$. A random point is picked in the area. The exact radius could be calculated with the knowledge of the fixed points and random point coordinates. A different random error of ε meters is added to each radius to reflect the error. Finally this overdetermined system is described in the following equation:

$$\begin{cases} (x_u - x_1)^2 + (y_u - y_1)^2 - (\sqrt{(x_1 - x_u)^2 + (y_1 - y_u)^2} \\ \qquad + \varepsilon_1)^2 = 0 \\ \quad \vdots \\ (x_u - x_N)^2 + (y_u - y_N)^2 - \\ \quad (\sqrt{(x_N - x_u)^2 + (y_N - y_u)^2} + \varepsilon_N)^2 = 0 \end{cases} \tag{1}$$

This system in this form is a non-linear least-squares problem. We use iterative non-linear least-squares algorithm to solve these equations due to distance mea-

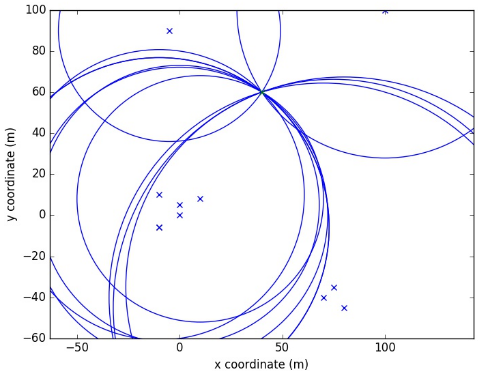

Figure 4: Optimal situation for 10 fixed points.

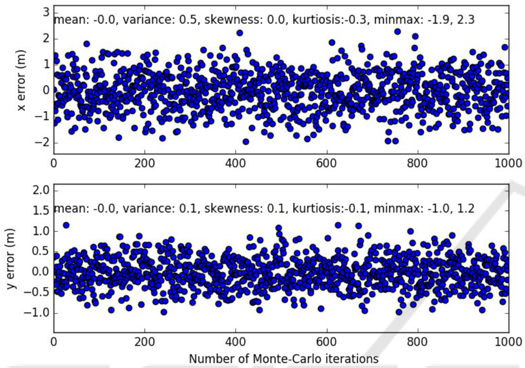

Figure 5: Example of the error repartition on x and y.

surement errors. In our simulation each ε_{n_wpt} is a random value between ± 2 meters. Using Python's scipy package, we iterate the process 1 000 times to act as a Monte-Carlo test and we repeat the process with 100 random and unknown points. Figure 4 represents the ideal situation with 10 well-known points. Figure 5 represents the error after 1 000 iterations for a given list of well-known points.

The results are presented in table 1 with regards to different number of fixed points. Δ_{max} is the difference between the maximum error and the minimum error for all the situations. So it is the upper bound of the error for all the situations (and iterations). $\Delta_{mean(\varepsilon_{\widehat{X}_u})}$ represent the upper bound of the mean of errors on one axis. $max(\sigma^2_{\widehat{X}_u})$ is the maximum of the variance in all the situations. $[\widehat{X}_u;\widehat{Y}_u]$ is a $N \times 2$ matrix size of all the estimation results of the unknown point.

We have started the iterative algorithm (least_squares() from the scipy Python library) from the same initial point and we experienced that the results were slightly different after the end of each iterative process. Therefore we executed the iterative process several times and we took the mean of the results. Our experience is that this mean value is of better quality than any of the standalone results.

In the following simulations, however, we considered that each distance measurement has a different measurement error. We consider that we only have one chance to calculate the unknown position to save power in the real case.

The main problem of this simulation is to help the algorithm to find the correct minimal solution. Optimisation functions are very susceptible to initial state. When the number of well-known points is not enough, a good solution is hard to find. That why the variances are very high for 4 and 5 fixed well-known points. Moreover, in 4 and 5 fixed points, we try to model a real grazing situation, so animals are really close. A group of reference points that are close to each other could behave as if they were one point. This situation is not suitable to estimate the position if no reference points are available that are far away from this group. The reason of this phenomenon is the small distance between the first points, the large distance to the last point, and the addition of a random error.

In conclusion, our simulation shows it is important to have at least 3 fixed points which are far away to be sure of the good problem resolution. This result is interesting to minimise the calculation load in an embedded system and to help us to evaluate the number of UWB anchors. Moreover, if a group of cows is close to each other, it is possible to activate only a part of the GPS receivers in the group to save power.

5.2 Effect of Reference Point Position Error

We consider using GPS to obtain the coordinates of the fixed points and to use UWB to measure the distance between the fixed points and the unknown point. In that case, the GPS error may introduce a more significant error source. We made a second simulation to understand the consequence of a GPS localisation error in the reconstruction of the unknown point. In this situation, we consider no distance measurement error.

The aim is to reduce the system to linear equations. The new system can be written as:

$$\begin{cases} (x_N - x_1)\cdot x_u + (y_N - y_1)\cdot y_u = \frac{1}{2}(r_1^2 - r_N^2 + x_N^2 \\ \quad - x_1^2 + y_N^2 - y_1^2) \\ \quad\vdots \\ (x_N - x_{N-1})\cdot x_u + (y_N - y_{N-1})\cdot y_u = \frac{1}{2}(r_{N-1}^2 - r_N^2 \\ \quad + x_N^2 - x_{N-1}^2 + y_N^2 - y_{N-1}^2)) \end{cases} \tag{2}$$

Table 1: Statistics on all the unknown point estimation in distance error situation in meter.

n_wpt	x (meter)				y (meter)			
pts	Δ_{max}	$mean(\varepsilon_{\widehat{X}_u})$	$\Delta_{mean(\varepsilon_{\widehat{X}_u})}$	$max(\sigma^2_{\widehat{X}_u})$	Δ_{max}	$mean(\varepsilon_{\widehat{Y}_u})$	$max(\sigma^2_{\widehat{Y}_u})$	$\Delta_{mean(\varepsilon_{\widehat{Y}_u})}$
4	23.6	-0.1	39	2.4	24.6	0.1	43.9	2.4
5	24.32	-0.1	37.8	3.8	23.6	0.0	43.0	4.0
6	12.5	0.0	5.5	0.3	14.8	0.0	7.8	0.3
10	9.7	0.0	2.9	0.2	9.9	0.0	2.7	0.1
20	6.2	0.0	1.2	0.1	6.4	0.0	1.0	0.1

This could be put in a matrix form (equation 3). Subtracting the last equation from the other equations is arbitrary.

$$\mathbf{G}\beta = \mathbf{F} \tag{3}$$

where $\mathbf{G} = \begin{bmatrix} x_N - x_1 & y_N - y_1 \\ \vdots & \vdots \\ x_N - x_{N-1} & y_N - y_{N-1} \end{bmatrix}$, $\beta = \begin{bmatrix} x_u \\ y_u \end{bmatrix}$, $F = \frac{1}{2} \cdot \begin{bmatrix} r_1^2 - r_N^2 + x_N^2 - x_1^2 + y_N^2 - y_1^2 \\ \vdots \\ r_{N-1}^2 - r_N^2 + x_N^2 - x_{N-1}^2 + y_N^2 - y_{N-1}^2 \end{bmatrix}$

The localisation estimation could be found with this linear equation using the standard linear least-squares method (eq. 4).

$$\widehat{\beta} = (\mathbf{G}^T\mathbf{G})^{-1}\mathbf{G}^T\mathbf{F} \tag{4}$$

$\widehat{\beta}$ is the estimated coordinate.

To visualize the problem, the figure 6 represents 10 fixed points with 1 000 different simulated errors added to them and the estimation of the unknown point. One larger patch in this figure represents a reference point with a set of error values added.

The results of this simulation are presented in table 2. For 10 fixed points in this configuration, the results are good. In some cases with few fixed points, this table show some variance problem. Sometime the simple resolution does not work and the result of the least-squares solution exhibits a large error. A low-pass filter that we did not implement could be used to control the problem.

The calculation takes approximately 20 to 50 seconds with the linear least-square method and 520 seconds to 715 seconds with the iterative non-linear algorithm proportion to the number of fixed points depending on the number of fixed points. The processor used is an Intel i7-4700MQ, 2.4 GHz and the computer is equipped with 16 GBytes of volatile memory.

We can conclude that linear least-square algorithm could be used if we have enough separate fixed points. If we have enough computation resources and not enough separate fixed points, we could use non-linear least-square techniques to find the correct unknown

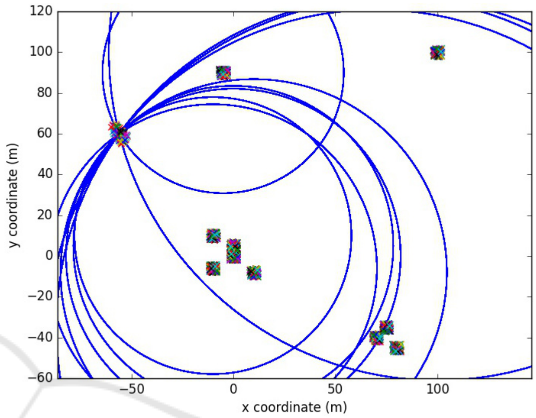

Figure 6: Representation of 10 fixed points with simulated error added to them and the effect of the error of the localisation of the unknown point.

point. We can see that for a same measurement error, in our case ±2 meters, with enough separated fixed points, the estimation is better if we assume that the measurement error is introduced into the fixed points' positions. In our real study, the distance measurement could be given by UWB which have, theoretically, a better accuracy than $\pm 2m$. Finally the error position could only depend on the effect of reference point position error. But we have to do other simulation and try.

6 ANGLE-BASED SHORT-RANGE LOCALISATION

Beside distance-based short-range localisation, we investigated whether we can build an in-house angle-of-arrival (AOA) short range localization system. This localisation method depends on a direction-sensitive antenna. The antenna rotates and finds out the angle of signals from stations with known locations. These stations can either be fixed to the ground or mounted to a moving platform which stops for long enough time periods so that it can be localised accurately (see section 3).

Our AOA localisation method is based on the prin-

Table 2: Statistics on all the unknown point estimation in fixed points error situation in meters.

linear least-squares solution

n_wpt	x (meter)				y (meter)			
pts	Δ_{max}	$mean(\varepsilon_{\widehat{X}_u})$	$\Delta_{mean(\varepsilon_{\widehat{X}_u})}$	$max(\sigma^2_{\widehat{X}_u})$	Δ_{max}	$mean(\varepsilon_{\widehat{Y}_u})$	$\Delta_{mean(\varepsilon_{\widehat{Y}_u})}$	$max(\sigma^2_{\widehat{Y}_u})$
4	$4 \cdot 10^6$	49.1	4341	$15 \cdot 10^9$	$4 \cdot 10^6$	-50.9	4473	$16 \cdot 10^9$
5	128.3	0.0	1.7	223.6	134.6	0.0	1.9	269.1
6	19.7	0.0	0.3	9.6	18.4	0.0	0.5	10.5
10	19.9	0.0	0.4	10.0	20.0	0.0	0.5	12.6
20	12.7	0.0	0.4	5.0	12.3	0.0	0.3	5.6

non-linear least-squares solution

n_wpt	x (meter)				y (meter)			
pts	Δ_{max}	$mean(\varepsilon_{\widehat{X}_u})$	$\Delta_{mean(\varepsilon_{\widehat{X}_u})}$	$max(\sigma^2_{\widehat{X}_u})$	Δ_{max}	$mean(\varepsilon_{\widehat{Y}_u})$	$\Delta_{mean(\varepsilon_{\widehat{Y}_u})}$	$max(\sigma^2_{\widehat{Y}_u})$
4	338	-0.1	5.9	178	370	0.1	189	
5	344.8	0.1	5.6	169.4	368.5	0.1	6.3	167.0
6	13.8	0.0	0.2	5.8	15.6	0.0	0.3	9.2
10	9.4	0.0	0.2	2.6	10.0	0.0	0.2	2.8
20	7.2	0.0	0.1	1.4	6.4	0.0	0.1	0.9

ciples described in (Cheung et al., 2006). We assume, however, that instead of the fixed stations measuring the angle of the mobile station's beacon signal, it is the mobile station that measures the angle of the fixed stations' beacon signal. So equation (47) in (Cheung et al., 2006) changes to equation 5.

$$tan(r_{AOA,i}) = \frac{sin(r_{AOA,i})}{cos(r_{AOA,i})} = \frac{y_i - y}{x_i - x} \quad (5)$$

where $r_{AOA,i}$ is the angle of the ith fixed station as measured by the mobile station, x_i, y_i is the known position of the ith fixed station, and $\beta = \begin{bmatrix} x_u \\ y_u \end{bmatrix}$ is the unknown position of the mobile station. By bringing this set of equations to a linear matrix form, we get

$$\mathbf{H} = \begin{bmatrix} -sin(r_{AOA,1}) & cos(r_{AOA,1}) \\ \vdots & \vdots \\ -sin(r_{AOA,N}) & cos(r_{AOA,N}) \end{bmatrix} \quad (6)$$

$$\mathbf{k} = \begin{bmatrix} -x_1 sin(r_{AOA,1}) + y_1 cos(r_{AOA,1}) \\ \vdots \\ -x_M sin(r_{AOA,N}) + y_M cos(r_{AOA,N}) \end{bmatrix} \quad (7)$$

where N is the number of the fixed stations whose angle is measured. N is at least 3 but the measurement may be overdetermined where $N > 3$ hence linear least-square solution is calculated.

$$\hat{\beta} = (\mathbf{H^T H})^{-1} \mathbf{H^T k} \quad (8)$$

We have made simulations to estimate the localisation accuracy. Figure 7 shows the localisation error measured in a simulation with varying angle measurement error and distance between the mobile station and the fixed stations. The 4 fixed stations were arranged in a square, the mobile station was from equal distance from all the fixed stations. The distance shown in the figure is the distance between the mobile station and any of the fixed stations. We assumed that there is a fixed measurement error (x axis). The angle measurement error was added to the exact angles so that the distance between $\hat{\beta}$ and β is maximal and this maximum error is shown in the figure.

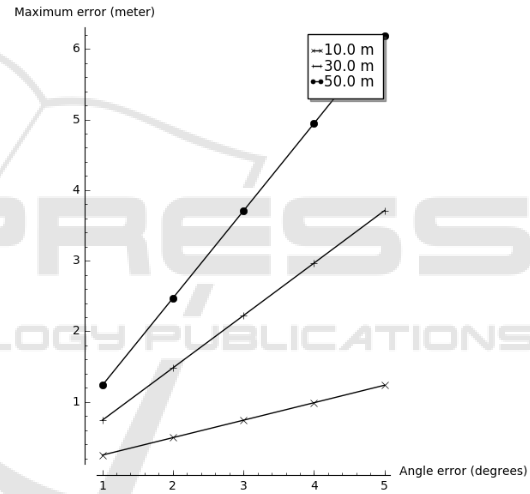

Figure 7: AOA localisation accuracy as a function of the distance to the fixed stations and angle measurement error.

With the distance of 50 meters, the required localisation precision can be achieved only if the angle measurement error is less than 1 degree. We built a simple prototype to verify how easily these requirements can be implemented based on Atmel ATmega328P MCU (Arduino Pro Mini) and Nordic nRF24L01P RF module, operating in the 2.4 GHz band. The sender unit was equipped with a simple omnidirectional stick antenna and the receiver unit was equipped with a 9 dBm PCB Yagi antenna. By turning around the Yagi antenna, the angle range (0 degree being the direction of the sender) was identified where the sender's data can be received. Unfortunately the nRF24L01P module has no Received Signal Strength Indicator (RSSI) feature, the signal is either present or not. This means that there is a minimum distance to the sender because if the receiver is closer to the sender than the minimal distance, the signal can be received independently of the angle of the receiver's antenna. This restriction can be mitigated by a receiver that provides RSSI along with the received data packets.

The measurements were made on an agricultural field that serves as a pasture. The sender's transmission power was set to one of the 3 levels the nRF24L01P supports. The receiver was located at a specified distance from the sender and the antenna was rotated. The angle when the signal appeared and when the signal disappeared was recorded. With this simple method the direction of the sender was identifiable with 1 degree precision. The minimum and maximum distances with different power levels were the following: PA_MIN: 4-20 meters, PA_LOW: 22-41 meters, PA_HIGH: 31-70 meters.

7 CONCLUSIONS

Low-cost, accurate localisation is often required in agricultural applications. We found that low-cost GPS modules are inadequate but in differential setup certain low-cost modules are able to produce the required accuracy if the target is stationary for at least 8-10 minutes. Certain cows (but not all of them) were found to satisfy the criteria for being stationary for 40-80 % of their grazing time. Movements have to be tracked by an auxiliary technology. We made simulations for two of such technologies: distance- and angle-based short-range localisation technology. In case of distance-based, the effect of distance measurement error results in worse position estimation than the effect of reference point measurement error. Angle-based short-range localisation turned out to be more cost-efficient but also more problematic, due to the rapidly growing localisation error as the distance between the mobile and the fixed station grows.

ACKNOWLEDGEMENTS

The Hungarian side of the research is supported by the AgroDat.hu project (project code: VKSZ_12-1-2013-0024), financed by the Government of Hungary. I thank ESEO for co-financing my research stay in Angers, France where part of the research was done. The French side of the research is financed by the region of ”Pays de la Loire” (Vagabond project).

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