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ZigBee-based wireless sensor network localization for cattle monitoring in grazing fields

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ABSTRACT

This paper presents the design of a localization scheme in wireless sensor networks (WSN) for cattle monitoring applications in grazing fields. No additional hardware was required for distance estimation since they were performed using the link quality indication (LQI), which is a standard feature of the ZigBee protocol. The ratiometric vector iteration (RVI) algorithm was implemented and modified to work with LQI measurements instead of the usual received signal strength indication (RSSI). Experimental results show acceptable localization performance given the requirements of usual cattle monitoring applications at low cost and low power consumption.

1. Introduction

In recent years, advances in wireless communication technologies and electronic systems miniaturization have contributed to the implementation of wireless sensor networks (WSN). A WSN is a system composed of several nodes, each node being a low-power-consumption and low-cost device equipped with one or more sensors, a processor, memory, a power supply and a transceiver (Yick et al., 2008). These nodes are capable of executing pre-programmed algorithms, exchanging data with other nodes and communicating with a master node. The feasibility of deployment of WSN's in open spaces to cover a wide area at low cost has made this technology very appealing for a number of applications such as surveillance (Arora et al., 2004), precision agriculture (Camilli et al., 2007; Morais et al., 2008) and cattle farming. In this later field, WSN's have started to be used in livestock control and monitoring applications such as virtual fencing for extensive grazing systems (Bishop-Hurley et al., 2007), animal behavior study (Nadimi et al., 2008a; Nadimi and Søgaard, 2009) and health monitoring (Schleppe et al., 2010).

In open space livestock monitoring, a relevant issue is to track the location of the animals in the field at a given time. Key aspects for the successful application of a WSN-based localization scheme in practical cattle farming are: low cost, due to the potentially high number of nodes required for monitoring an entire herd of cattle; efficient energy management, in order to provide the system with a reasonable operation time; and independence from additional hardware which can rise costs and reduce mobility and robustness of mobile devices. One of the most popular systems for outdoors localization is the global positioning system (GPS) (Schlecht et al., 2004; Barbari et al., 2006; Schwager et al., 2007; Schleppe et al., 2010); however, this approach has drawbacks such as high energy consumption and cost, which makes it less suitable for its use in applied cattle farming (Nadimi et al., 2008b). As an alternative, there exists a wide variety of localization algorithms where the initially unknown locations of the sensor nodes are estimated by using knowledge of the absolute position of a few other nodes called "anchors" and measurements of distance and/or orientation with respect to neighboring nodes. In concordance with the technique used for estimating the distance or the relative position between neighboring nodes, algorithms can be classified in three broad categories (Baronti et al., 2007): angle of arrival (AOA) of the received messages, time difference of arrival (TDOA) and link signal-strength-based techniques. AOA and TDOA-based localization methods offer a very good precision, but they require additional hardware and have relatively high energy requirements (Wang et al., 2009). On the other hand, signal-strength-based methods employ measurements of the received signal strength indication (RSSI), provided by most wireless network devices; consequently, these methods require no additional

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hardware nor increments in energy consumption, size or cost (Mao et al., 2007b). Distance between nodes can be estimated on the basis of measured received power, known transmit power and a propagation power loss model. The main disadvantage of this technique is the presence of errors introduced by variations in the propagation model, which is strongly dependent of environmental characteristics such as obstacles that can attenuate and reflect signals.

Some existing signal-strength-based sensor localization methods use advanced algorithms like particle filters (Yun and Kim, 2007), genetic algorithms (Zhang et al., 2008) or a combination of soft computing tools (Yun et al., 2009). Although these approaches can provide high localization precision, their high computation requirement and communication overhead makes them not appropriate for applications in low cost and low power devices (Lee et al., 2006). In order to improve localization efficiency in networks with few available anchors, or where it is impossible to distribute them properly, the use of mobile anchors has been proposed (Baggio and Langendoen, 2008; Caballero et al., 2008; Xing-Hong et al., 2008). However, the use of anchors carried by an autonomous robot or other means is expensive and difficult to implement in applications such as cattle monitoring in grazing fields. On the contrary, less complex localization techniques, such as multilateration using RSSI measurements and a simple propagation model (Wang et al., 2009), are still effective in some specific applications. In the field of cattle farming, Nadimi et al. (2008a) employ a ZigBee-based WSN to estimate the distance of the animals from a single gateway, attempting to calculate their velocities. In another work, Nadimi et al. (2008b) use a similar scheme for detecting the presence and estimating the residency time of animals in a grazing area. Although the later two schemes do not exactly address the localization problem, they validate the use of signal-strength-based algorithms for estimating distances between nodes in grazing fields. One of the several existing localization algorithms is the ratiometric vector iteration (RVI) proposed by Lee et al. (2006). This method takes into account the limitations of WSN nodes regarding computational capacity and energy use, achieving a good localization precision with low communication overhead. Therefore, RVI appears as a very convenient option for WSN-based localization in applied farming, given the cost, energy and hardware constraints of this problem.

This work has focused in the implementation of the RVI algorithm for sensor localization in an open space, as the first stage in the development of an experimental cattle monitoring system. For this purpose a WSN was established using JN5139 IEEE 802.15.4/ZigBee-compliant wireless microcontrollers from Jennic. Instead of RSSI, these devices feature the similar link quality indication (LQI). There are few reports of LQI measurements being used for estimating distances in WSNs; hence, in this work the feasibility of using LQI for this purpose was evaluated.

The model required for estimating distance from measurements of RSSI or LQI strongly depends on the transmission and reception characteristics of the wireless devices and the properties of the communications channel, specially the path loss exponent (Mao et al., 2007a). Although nodes of a WSN are similar to each other, in practice they can differ in characteristics such as antenna gains or transmit power, thus introducing errors in distance estimations.

2. Materials and methods

2.1. Jennic JN5139 wireless microcontroller

Jennic JN5139 wireless microcontrollers (Jennic Ltd., 2008a) were used for the experiments in this paper. Two different models were used: the JN5139-Z01-M00 with integrated antenna and the high-power JN5139-Z01-M02 with a Titanis omnidirectional SMA antenna from Antenova. The JN5139 is a low-cost, low-power device (about 1.2 μA in *sleep* mode) with a 32-bit processor and a 2.4 GHz IEEE802.15.4/ZigBee compliant transceiver. The JN5139's transceiver provides an LQI measure which was employed for distance estimation. The transmit power of the JN5139 can be set in 5 different levels with increments of 6 dBm ranging from −30 to 0 dBm for the JN5139-Z01-M00 and from −12 to 18 dBm for the M02. All the nodes used in the experiments were configured to transmit at the maximum available power level. The power supply for the devices was provided by 6 V – 4200 mAh batteries through an integrated 3.3 V voltage regulator, allowing continuous operation for about 3 days; nonetheless, this period can be extended by using the power saving features of the transceivers. The programming of the devices was carried out using an application programming interface (API) developed by Jennic that enables the user to easily control network functions and integrated peripherals. To analyze the packet loss when the link is established, the software application described in Jennic (2008) as complement of their module JN5139 was used. This application provides an indicator called PER. No packet losses occur if the PER indicator presents a low value. A value close to 30% makes the link non-viable.

2.2. ZigBee wireless sensor network

There exist three types of devices in a ZigBee network: coordinators, routers and end devices (ZigBee Alliance, 2007). In this article, a WSN composed of the following elements is considered:

- A network coordinator implemented with a JN5139-Z01-M02 device, connected through an UART interface to a PC in which data was registered and the localization algorithm was executed.
- Four JN5139-Z01-M02 devices used as routers. These nodes were fixed at known locations and were used as anchors for the localization algorithm. At least one of the fixed nodes must be located within the range of the coordinator and all of them must be within the range of another router connected to the network.
- One JN5139-Z01-M00 end node. The end node, which we will refer to as "sensor node", is mobile and the problem consists in determining its location.

Modules JN5139-Z01-M00 contain an embedded ceramic antenna which allows to encapsulate the device in a low weight-small size plastic container without external components, allowing that the eartag weights only 50 g. The 6 dB mote radio achieves a range of 200 m in laboratory environment. All the ZigBee modules use a radio in the 2.4 GHz band, according to Chilean telecommunications regulations. For purposes of the experiment mobile nodes were configured to wake up every 2 min and sequentially communicate with each of the four anchor nodes.

The anchors used in the experiments were all cased in plastic boxes, together with their corresponding antennas and power supplies, as shown in Fig. 1a and c, while the sensor node was enclosed in a lightweight ear tag suitable to be worn by the cattle, as depicted by Fig. 1b and d. Each of the cases containing the anchors was mounted atop 2 m wooden poles and the sensor node was attached on a 1 m and 20 cm height mobile support.

The network was installed in the grazing field shown in Fig. 2. The network layout is depicted by Fig. 3, where the anchor nodes are designated by AN1–AN4. The anchors were placed in the vertices of a square of side length D, where the sensor node's movements were restricted. The selection of the distance D, which determines the separation between anchors, was made taking the following aspects into account: cost, practical restrictions and desired performance of the localization algorithm. In general, shorter distances lead to better localization precision (Mao et al., 2007b); however, this implies higher costs due to the increase in the number of anchors required to cover a given area. This paper is oriented to

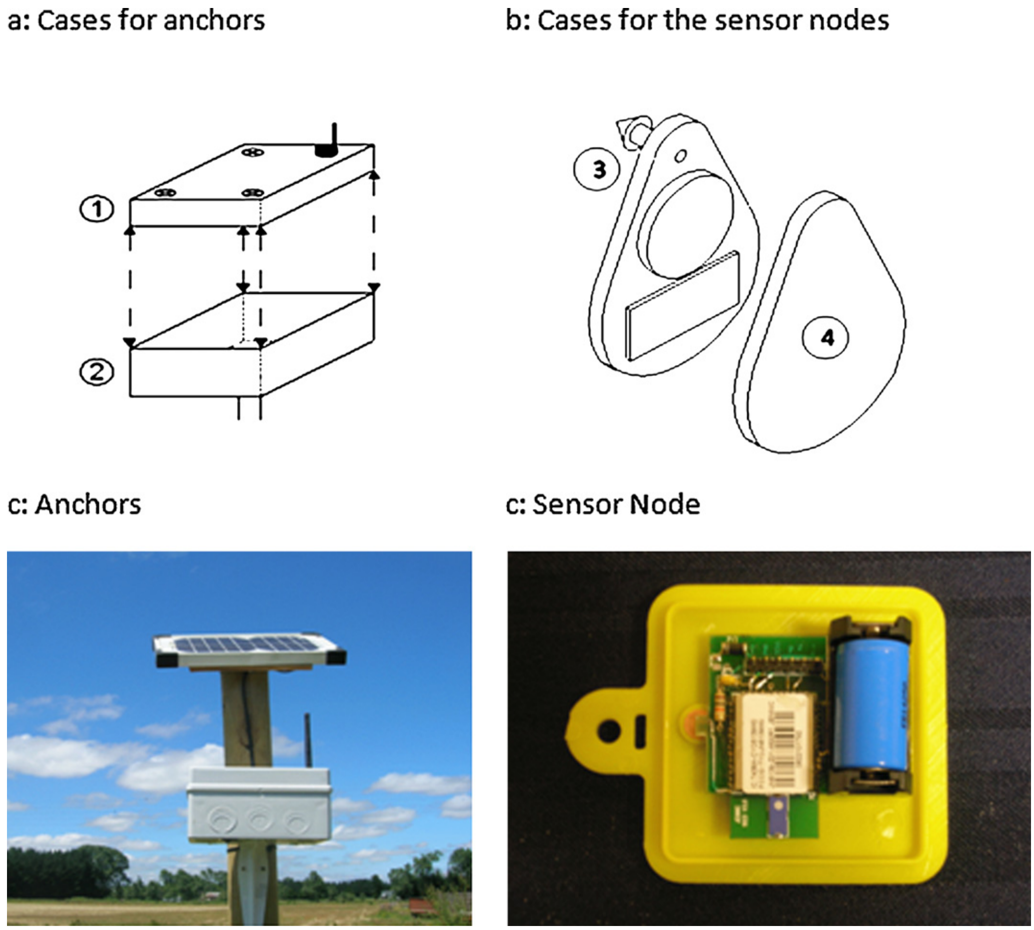

Fig. 1. Cases used for mounting the transceivers.

a cattle monitoring application where the localization precision requirements are not high; therefore, the design criterion for distance *D* was mainly based on the economic and practical aspects. The separation between anchors is upper limited by the communication range of the devices, which was determined through field experiments (Jennic Ltd., 2008b) to be 220 m with transmit power of 0 dBm. In order to improve the communication robustness to obstacles, terrain irregularities and other disturbances, the devices were distributed with a separation $D = 80$ m, close to the 35% of their maximum communication range. This configuration guarantees that the sensor node is always simultaneously within the range of the four anchors; furthermore, it involves a reasonable implementation cost and avoids the need of installing a greater number of anchors, which might obstruct the free displacements of the cattle in the field.

In real scale, anchors work as routers generating a scalable fully connected network that allows interconnecting different grazing fields.

2.3. Link quality indication (LQI)

The LQI measurement is a characterization of the strength and/or data quality of a received packet. The IEE802.15.4 standard (IEEE Computer Society, 2006) indicates that, for each received

Fig. 2. Test field used for experiments.

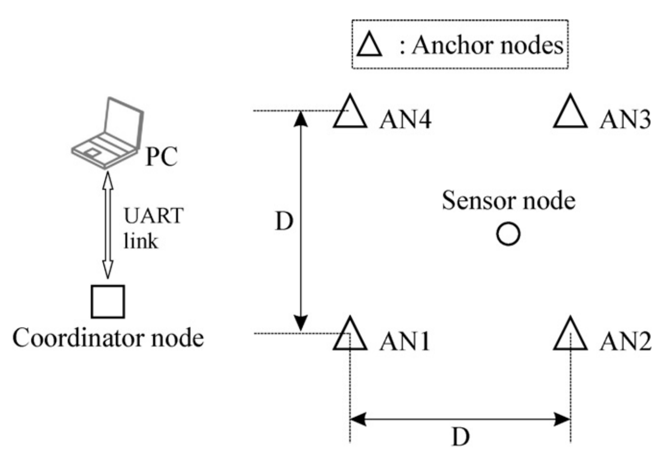

Fig. 3. Scheme of the implemented ZigBee network.

packet, the LQI shall be measured and represented as an integer ranging from 0 to 255. The minimum and maximum LQI values are associated with the lowest and highest signal qualities detectable by the receiver. In the case of the JN5139, the LQI is represented as 44 values uniformly distributed between 0 and 255.

2.3.1. Relationship between LQI and distance

In this work we aim at estimating distances in a WSN starting from LQI measurements; for this purpose a suitable model is required. Models that relate LQI and distance are scarce in the literature; however there exist several models for the received signal strength (RSS) that could be adapted for LQI. We evaluated two models: a log-normal (Mao et al., 2007a) and an exponential model (Lee et al., 2006).

The log-normal is a widely used model that is presented in the following equations:

$$P_{ij}\,[\mathrm{dBm}] \sim N(\overline{P_{ij}}\,[\mathrm{dBm}], \sigma^2_{\mathrm{dB}})$$
$$\overline{P_{ij}}\,[\mathrm{dBm}] = P_{0,j}\,[\mathrm{dBm}] - 10\alpha \log_{10}\left(\frac{d_{ij}}{d_0}\right), \qquad (1)$$

where P_{ij} [dBm] is the received power at a receiving node i from a transmitting node j in dB milliwatts, $\overline{P_{ij}}$ [dBm] is the mean power in dB milliwatts, σ^2_{dB} is the variance of the shadowing, $P_{0,j}$ [dBm] is the received power in dB milliwatts at a reference distance d_0 from the transmitter j, α is the path loss exponent, and d_{ij} is the distance between nodes i and j. Although this model could be adapted to use LQI instead of received power, the simultaneous calibration of its main parameters $P_{0,j}$ and α is a challenging task. The path loss exponent α is strongly influenced by the environmental conditions (Mao et al., 2007a), which include terrain characteristics, presence of obstacles, humidity, etc. And the second parameter, $P_{0,j}$, depends on several characteristics of each transmitter such as antenna properties, antenna orientation and transmit power level which can differ from one transmitter to another, even using nodes of the same brand and model.

On the other hand, a simpler exponential model proposed by Lee et al. (2006) has the following form:

$$r_{ij} = \frac{a}{{d_{ij}}^{\alpha}} + n_i, \qquad (2)$$

where r_{ij} is the sensed RSS value in the ith sensor from the jth transmitting node. This work proposes to use the same relation (2), assuming the r_{ij} corresponding to the LQI obtained from the link between nodes i and j. This is done because the ZigBee standard does not bind the manufacturer to provide the RSSI as it does for the LQI (Baronti et al., 2007). a (similar to $P_{0,j}$) is the signal strength at the transmit source and n_i is white Gaussian noise. The remaining parameters, d_{ij} and α, have the same meaning as in model (1). A relevant feature of the exponential model is that, disregarding the noise in Eq. (2), it is possible to consider a relative distance ratio r_{ij}/r_{ik}, $(j \neq k)$ to eliminate the dependence on a. This simplifies the model calibration procedure but might also introduce errors if the power-related parameter a differs between one node and another, which is common in practice. However, this situation is acceptable if the network comprises many nodes and their individual characterization is unpractical. The calibration procedure for α in Eq. (2) is presented in the following section.

2.3.2. Estimation of the path loss exponent

Path loss exponent α was estimated by fitting the model of Eq. (2) to an experimental data set using a least squares method included in the curve fitting toolbox from MATLAB R2006a. The experiment performed to obtain the data set was carried out using two devices: a fixed high-power JN5139-Z01-M02 acting as transmitter and a mobile JN5139-Z01-M00 acting as receiver; the distance between the transceivers was initially set to 2 m and a series of 15 messages were sent from the transmitter to the receiver. The capture of 15 measurements of LQI from the anchors requires tenths of sec. This is a reduced time considering the future use in animals. The mean LQI throughout the transmission was recorded and the distance between the devices was incremented by 2 until reaching 140 m, repeating the transmission and LQI measurements in each step.

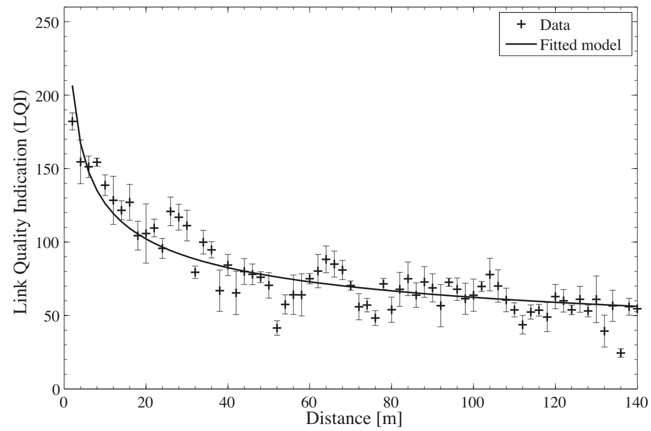

Fig. 4. Mean LQI vs. distance for the fitted propagation model and experimental data. Error bars indicate the standard deviation at each point. Anchor node at 2 m height and sensor node at 1 m height.

Fig. 4 shows the experimental data set and the result of the model fitting to this data (r = 0.88). The optimal model parameters obtained by this method were α = 0.30 and a = 255.

The ear tag was fixed to a 1 m high mobile support given that it corresponds to the high of ear tag of an erected animal. However, to obtain the estimated distances we used a model relating LQI and distance. The model was calibrated with field data using a fix node (anchor) located 2 m high and a mobile node (sensor node) located 1 m high, using variable distances from 2 to 140 m. The experiment was repeated with the sensor node to a height of 20 cm above ground level, (the approximate location of the ear of a grazing animal). This complements previous experiment where the sensor node was located 1 m above ground (ear height of the animal in standing position). Grass height varied between 10 and 15 cm. The alpha coefficient relating distance and LQI obtained in both cases did not vary significantly (resulting in a value around 0.30 and 0.28), validating the use of the technique independent of the position of the animal's head.

In the experiments shown in Figs. 4 and 5, the PER index began to be nonzero only at the 100 m distance. At 120 m the reported rate of data packet loss was 10%. The experiments shown in Figs. 4 and 5 were conducted in winter days (partly cloudy, with relative humidity of about 80%, during the morning, with the presence of dew on the grass). These experiments showed that the relationship between distance and LQI was kept while the heights of sensor node were 1 m and 20 cm.

2.4. Localization algorithm

The localization method implemented in this study is based on the ratiometric vector iteration (RVI) proposed by Lee et al. (2006). Let X and X_j be the true location of the sensor node and its estimated location at the jth iteration of the algorithm, respectively. Taking into account the locations of k ($k \geq 3$) anchors, $(S_1, \ldots, S_k)$, and a set $(g_1, \ldots, g_k)$ of estimates of the distance between each anchor and the sensor node, the goal of the RVI is to update X_j in such a way that the difference between the ratios $\left|\overrightarrow{S_1X_j}\right| : \ldots : \left|\overrightarrow{S_kX_j}\right|$ and $g_1 : \ldots : g_k$

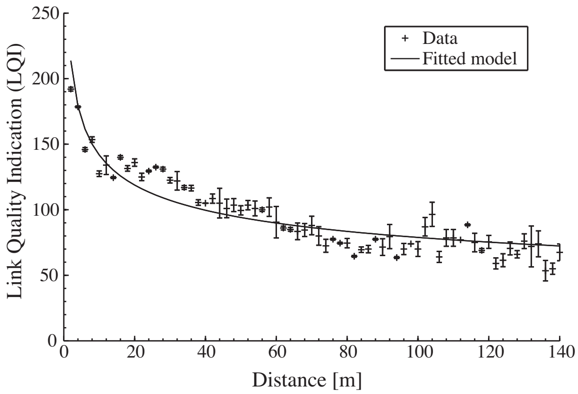

Fig. 5. Mean LQI vs. distance for the fitted propagation model and experimental data. Error bars indicate the standard deviation at each point. Anchor node at 2 m height and sensor node at 20 cm height.

decreases. This update is performed by means of a so called "move vector" $\vec{V_j}$ that is added to X_j in each iteration. In the original version of the RVI algorithm, the g_i were calculated using RSSI measures. In this work the aim was to determine g_i by estimating the distance d_i between the sensor node and the anchor i as a function of LQI starting from Eq. (2). For the purpose of comparison, the estimated distances were normalized by the sum $\sum_{i=1}^{k} d_i$, as suggested by Lee et al. (2006). The equation used for obtaining g_i was the following:

$$g_i = \frac{d_i}{\sum_{i=1}^{k} d_i} = \frac{\bar{L}_i^{-1/\alpha}}{\sum_{i=1}^{k} \bar{L}_i^{-1/\alpha}}, \tag{3}$$

where $\bar{L_i}$ is the mean of 15 LQI measures registered by the sensor node throughout communication with anchor i.

The steps of the modified RVI algorithm implemented in this paper are given as follows:

1. *Initialization*: The initial guess of the sensor node's location, X_0, was obtained as the weighted centroid of the anchors' locations $(S_1, \ldots, S_k)$ with weights $(w_1, \ldots, w_k)$ depending on the proximity of the sensor node to each anchor and characterized by

$$w_1 : \ldots : w_k = \frac{1}{\left|\overrightarrow{S_1X}\right|^{\beta}} : \ldots : \frac{1}{\left|\overrightarrow{S_kX}\right|^{\beta}} = \bar{L}_1^{\beta/\alpha} : \ldots : \bar{L}_k^{\beta/\alpha}, \tag{4}$$

where again Eq. (2) was used for estimating distances $\left|\overrightarrow{S_iX}\right|$; β determines the relationship between distance and weights, which can be inverse ($\beta = 1$), square inverse ($\beta = 2$), etc. The location estimated by the weighted centroid, X_{WC}, is given by:

$$X_{WC} = \frac{\sum_{i=1}^{k} w_i S_i}{\sum_{i=1}^{k} w_i}. \tag{5}$$

2. *Normalization*: In order to be compared to $g_1 : \ldots : g_k$, the ratio $\left|\overrightarrow{S_1X_j}\right| : \ldots : \left|\overrightarrow{S_kX_j}\right|$ is normalized by the sum $\sum_{i=1}^{k} \left|\overrightarrow{S_iX_j}\right|$, and is expressed as follows:

$$\left|\overrightarrow{S_1X_j}\right| : \ldots : \left|\overrightarrow{S_kX_j}\right| = g_{1,j} : \ldots : g_{k,j}, \quad \text{where} \quad g_{i,j} = \frac{\left|\overrightarrow{S_iX_j}\right|}{\sum_{i=1}^{k} \left|\overrightarrow{S_iX_j}\right|} \tag{6}$$

3. *Move vector calculation*: The move vector $\vec{V_j}$ is given by

$$\vec{V_j} = \begin{cases} c\dfrac{\vec{\Delta}_j}{\left|\vec{\Delta}_j\right|} & \text{if } j > N_{init} \quad \text{and} \quad \left|\vec{\Delta}_j\right| < c \\ \vec{\Delta}_j & \text{otherwise,} \end{cases} \tag{7}$$

$$\vec{\Delta}_j = \sum_{i=1}^{k} (g_i - g_{i,j}) \frac{\overrightarrow{S_iX_j}}{\left|\overrightarrow{S_iX_j}\right|},$$

where c is a constant that imposes a minimum step size after N_{init} iterations in order to reduce the number of iterations required for convergence. In the first N_{init} iterations, the step size is allowed to be smaller than c so that iteration vector can progressively change its direction towards the target location. The component $\overrightarrow{S_iX_j} / \left|\overrightarrow{S_iX_j}\right|$ is a unit vector used for indicating the direction of the move vector, which magnitude is given by the difference between ratios $(g_i - g_{i,j})$.

4. *Update*: The location estimate in the $j+1$-th iteration is given by

$$X_{j+1} = X_j + \vec{V_j}. \tag{8}$$

5. *End*: The algorithm stops if at least one of the following conditions is met

$$\overrightarrow{V_{j-1}} \cdot \vec{V_j} < 0 \quad \text{or} \quad \left|X_{j+1} - X_j\right| < C_{th}, \tag{9}$$

where C_{th} is the threshold for terminating the algorithm. The conditions given by (9) imply that the algorithm stops when the direction of $\vec{V_j}$ drastically changes from one iteration to the next, or if the move distance at the jth iteration becomes smaller than C_{th}. On these termination conditions, the RVI returns X_{j+1} as the location estimate of the sensor node. Otherwise, the index j is incremented and the algorithm goes back to step 2.

The RVI algorithm was implemented in MATLAB running on a PC with a Pentium 4 processor.

Table 1
Design parameters of the localization algorithm.

Parameter	Value	Parameter	Value
α	0.3	c	1
β	1	c_{th}	0.1
N_{init}	5		

3. Results and discussion

The performance of the proposed localization method was evaluated using the network described in Section 2.2 with 6 different sensor node locations; the design parameters of the localization algorithm are displayed in Table 1.

Fig. 6 shows the starting point (initial guess) of the localization algorithm, the sequence of estimates throughout the algorithm's iterations and the localization error for each one of the 6 cases considered in the experiment. From Fig. 6 it can be observed that the algorithm does not reach the real position in dataset 4. In this case the initial and final positions are far away from the anchor. Here the estimate of the distance using LQI is not too good (see Figs. 4 and 5) which might be the cause for the poor behavior of the algorithm. However, the location error was kept in bounds. In Fig. 6 it can be observed that a farther starting position requires more iterations to reach the final position (see dataset 6). On the other hand, the idea is to use the last calculated position of the animal as a starting value. This could result in reducing the number of iterations in case of small displacements of the animals in the field.

The parameter c in Eq. (7) allows modifying the convergency rate. The smaller c, the slower the convergency rate. In our experiments we used because the algorithm always converged with the

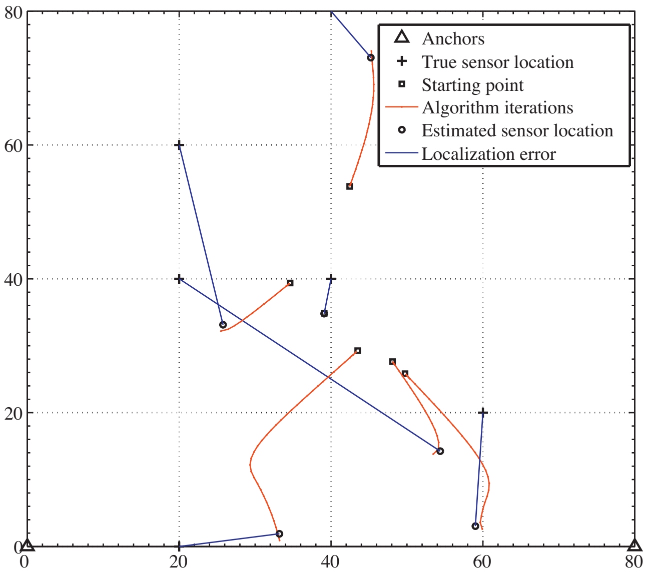

Fig. 6. Experimental results of the LQI-based localization using a modified RVI algorithm.

available data and required a smaller number of iterations to find the solution.

Stop conditions are two, represented in Eq. (8). The first condition prevents the algorithm from changing direction. The second condition (·) is equivalent to (see Eq. (8)). This is a condition showing that the algorithm reached a solution with a precision given by the parameter C_{th}. These two stop conditions were proposed by Lee et al. (2006). We consider that with these conditions the location normally determined is sufficiently precise for the objectives of this work. More iterations will require more connections and consequently more energy.

Table 2 contains the true and estimated location for each case as well as the number of iterations of the algorithm and the localization error. The localization error, calculated as the Euclidean distance between the true and the estimated location of the sensor, ranged between 5.2 and 43.0 m, with a mean of 19.1 m. The number of iterations required for convergence of the algorithm was between 1 (in case 3) and 39 (in case 6).

Results showed that the localization accuracy had a great variability and was lower than expected. Nonetheless, in 4 out of 6 cases the error was below 20 m and the convergence of the algorithm took a reduced number of iterations.

In this work we progressed in the generation of low-cost applications, with efficient management of energy and which do not require additional hardware to reduce mobility (weight) and thus increasing the robustness of the system. In this context it is sufficient to support a ground observer for an approximate location of an animal in the pasture.

This system is not intended to replace the GPS but to provide a solution that can be used for tracking purposes in pastures of cattle and to comply with weight requirements and energy independence to be used as a tag on the animal's ear.

Table 2
Details of the experimental results.

Case No.	True location [m]	Estimated location [m]	Iterations	Error [m]
1	(40, 80)	(45.3, 73.1)	26	8.7
2	(20, 60)	(25.8, 33.2)	17	27.5
3	(40, 40)	(39.1, 34.8)	1	5.2
4	(20, 40)	(54.4, 14.2)	21	43.0
5	(60, 20)	(59.0, 3.0)	32	17.0
6	(20, 0)	(33.2, 1.9)	39	13.3

We must highlight that due to the innovation in using the LQI instead the RSSI the obtained alpha value is very low compared to Lee et al. (2006); however, this does not affect the performance of the location algorithm.

Finally, in our approach, the sensor nodes enter dormancy at regular intervals. For experimental purposes, as a way to speed up the measurements, this interval was set to a minimum of 2 min. Results allow to install the sensor nodes in cows, increasing the latency period to 20 min with the objective to increase the sensor node life time to around 1 year using a lithium-ion battery (3.6 V, 1/2 AA, 1200 mAH).

4. Conclusions and future work

The study carried out in this paper showed that the LQI-based RVI algorithm has the potential to be a useful tool for outdoors localization in cattle monitoring applications. The design of the localization system was performed taking key aspects into account such as cost, weight and energy consumption. The resulting scheme was able to obtain a mean localization error in the order of 20 m, which is reasonable for a basic cattle monitoring system, while keeping hardware costs and communication overhead low. However, in a future implementation of this technology the localization precision and the overall robustness of the system against environmental fluctuation should be improved. We believe that this can be achieved by increasing the reliability of the LQI measures used as input of the localization algorithm by implementing a more adequate method for filtering and prediction of this indicator in noisy and time-varying environments given by changes in air humidity, dew, and temperature. The experiments did not consider live animals, task that must be considered in future work.

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