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Cooperative Distance Classification using an IEEE 802.15.4-compliant Transceiver

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***Abstract*—In this paper we consider the problem of how several *observer nodes* can cooperatively make reliable judgements about one *mobile node*. These judgments shall not only cover the mere presence or absence of the mobile node, but also include coarse indications about the distance of the mobile node to the observers. To this end, we present and investigate in this paper a scheme for *distance classification*. The results show that our scheme greatly reduces the number of times where the mobile node is classified as "absent" and furthermore provides reliable classifications into one of a set of pre-defined distances, provided this pre-defined set is small enough.**

I. Introduction

It is often desirable to keep a group of things (a "herd") together. This can for example be a group of persons like a school class on a trip, or it can be a collection of items that shall be transported together. By "keeping a group together" we mean that group members should be geographically close to other group members. Any violation of this "togetherness" is considered important and should be detected.

We are currently working on a system (the *herding system*), in which to each person or item a wireless sensor network (WSN) node is attached. The WSN nodes form a multi-hop network, and checking the togetherness of the group is then related to the connectivity of the network. Each WSN node periodically broadcasts "hello" packets (called *beacons* from now). Each node in the network is responsible for *monitoring* some of its neighbor nodes. By monitoring we mean that the monitoring node A has to check for the presence or absence of beacons of a monitored node X. The monitoring results are used to make an inference about the presence or absence of node X, and in case of its absence, to trigger actions like a network-wide search for X. Additionally, we also want to obtain some hints about the distance that node X has to A. However, it is not our goal to measure the geographical distance between A and X with high precision, as we do not want to deal with the notoriously hard issue of ranging [1], [2]. Instead, we aim to *classify* the current distance to node X into one of a few pre-defined distance classes (one informal example could be a classification into "near", "far", "away" and "X is somewhere but i cannot tell reliably enough"). This allows node A to operate in different modes of "alertness": when node X is classified as being near, node A needs to receive fewer of X's beacons and can spend more time in sleep state. On the other hand, when node X is "far" or "somewhere", node A must listen more carefully for X's beacons to detect its disappearance as quickly as possible.

In this paper we consider a scheme that achieves this classification in three steps, using an IEEE 802.15.4-compliant physical layer. In the first step, each monitoring node A performs local preprocessing of the beacons received from X to smooth out random channel fluctuations – the major observables used here are the RSSI and LQI values attached to packets and the beacon loss rate. In the second step, the monitoring node A performs distance classification based on an artificial neural network (ANN), applied to the output of the first step. In the third step, node A exchanges its observations about X with other nodes monitoring X. By this, node A can include its neighbors observations to improve its classification. We refer to this as *cooperation*. We provide an experimental investigation of the effectiveness of the cooperation-based classification scheme under idealized conditions. The results indicate that reliable classification is indeed possible, provided that the number of distances into which to classify is small. Furthermore, the cooperation greatly helps to avoid situations in which a present mobile node is classified as "away", but surprisingly has adverse effects on the rate of false distance classifications.

While in general the topic of cooperative information fusion and decision / classification is a widely researched topic in wireless sensor networks [9], to the best of our knowledge the approach to use distance classification instead of ranging has not been considered before in the realm of wireless sensor networks. Consequently, we are also not aware of any works in which this has been done cooperatively. Traditionally, the work on localization and ranging attempts to estimate the precise distance [10], [1], [2] using, for example, signal strength, time (difference) of arrival or angle of arrival as basic measures. The ranging based on signal strength indication, which is readily possible with commercial IEEE 802.15.4 transceivers, is known to be very unreliable [1].

This paper is structured as follows. In the following Section II we explain the measurement setup and scenario. In Section III we describe our classification scheme, and in Section IV we experimentally assess its classification performance. Our conclusions are offered in Section V. An extended version of this paper is available as a technical report [3].

II. Measurement setup

A. Sensor node platform

The sensor node platform is the Tmote Sky from MoteIV Corporation [4]. It contains a Texas Instruments MSP430 microcontroller, a Chipcon CC2420 IEEE 802.15.4-compliant radio transceiver [5] and a USB port for programming and data collection. It has an integrated omnidirectional antenna

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on the board attaining a 50-meter range indoors and a 125-meter range outdoors. The CC2420 radio transceiver has programmable output power.

The IEEE 802.15.4 standard [6] prescribes that the physical layer provides for each received packets two different values: a *received signal strength indicator* (RSSI) and a *link quality indicator* (LQI). The eight-bit RSSI value is equivalent to the strength of the received signal in dBm. With respect to the LQI value, the ChipCon transceiver calculates an average correlation value, the *chip correlation indicator (CCI)*, for each packet based on the first eight symbols following the start of frame delimiter. The larger this value the better.

B. Experiment setup

There are seven stationary nodes arranged in a line, the distance between neighbored nodes is below ten centimeters. These nodes are called the *observer nodes*. An eigth node, referred to as the *mobile node* is placed at a certain distance to the observer nodes and then transmits 5000 beacons in a row with a beacon spacing of 50 msec and a fixed transmit power level. The observer nodes do nothing else than receiving those packets and forward them, together with important meta-information (packet LQI and RSSI value, observer node identification, sequence number of the beacon packet, timestamp, transmit power level) over a serial interface to a laptop, which stores the results in one tracefile per observer node. All evaluations are later done offline.

The measurements have been done in an outdoor scenario. The interference situation at the experiment site is not known. Different distances between the mobile node and the observer nodes have been used: from 5m to 55m in steps of 5m. The measurements have been repeated with different transmit power levels of -5 and -7 dBm. However, in this paper we will report only the results for the -5 dBm power setting. The results and trends for the -7 dBm case are similar and reported in the technical report [3].

III. Distance classification scheme

The goal of the classification scheme can be described as follows: a node A shall use its own observations about another node X and possibly also the observations of other nodes about X in order to assign to X one label out of the following set of labels:

$$\{d_1, \ldots, d_m, \infty, U\} \tag{1}$$

where $\{d_1, \ldots, d_m\}$ is a small set of pre-selected distances (for our measurements we have $\{d_1, \ldots, d_m\} \subset \{5\text{m}, 10\text{m}, \ldots, 55\text{m}\}$), ∞ denotes node A's opinion that node X has disappeared, and U refers to an an undecided state, in which node A receives packets from X but is not able to classify the distance with a sufficiently high confidence value.

The classification scheme consists of three different steps. In the *reception step* an observer node updates its local statistics about the mobile node. This happens either upon reception of an incoming packet or upon the converse event of not receiving a packet when it actually should have received one (due to the assumed periodicity of the beacons such a conclusion can be drawn after a timeout). In the *classification step* the observer assigns one of the labels introduced above based on its current local statistics. In the final *cooperation step* the observer nodes exchange their classification results and create a refined classification.

We discuss these steps in turn. We have investigated different approaches for each of these steps, but we have always taken great care to take into account the constraints of the sensor nodes (computational power, memory, packet sizes), which put severe limits on the complexity of estimation schemes.

A. Reception step

In the reception step the information obtained from incoming packets (RSSI and LQI values) as well as the presence or absence of packets are preprocessed. The preprocessing scheme should be adaptive in order to accommodate instationary observations caused by node mobility, and it should eliminate the noise found in RSSI and LQI measurements.

In this paper, we restrict to three observables: an observer node continuously estimates the average LQI value, the average RSSI value and the current packet loss rate. In the report [3] also the variance of RSSI and LQI have been considered as input to the classification, but they do not improve the classification performance, so we do not consider them here. For the LQI and RSSI averages we have adopted exponential moving average estimators:

$$\bar{x_n} = \alpha \bar{x_{n-1}} + (1 - \alpha) x_n \tag{2}$$

where $\bar{x_n}$ represents the current estimate, $\bar{x_{n-1}}$ the previous estimate, x_n the new observation and $\alpha \in (0, 1)$ is an adjustable parameter that allows a tradeoff between "stability" and "agility" of the estimator. We have used $\alpha = 0.92$, so that most weight is put on the history and only little weight on the new observation. For the computation of the average packet success we have also adopted the exponential moving average scheme with using $x_n = 1$ for a received packet and $x_n = 0$ for a lost packet (after a timeout).

For the LQI and RSSI values one important question is how to deal with lost packets. We have decided to not represent lost packets in the calculation of RSSI and LQI averages.

B. Classification step

The goal of the classification step is to classify the current distance of a node into one of a small set of possible distances (including ∞ and U, see Equation 1) based on the current estimates of RSSI and LQI averages and the current estimate of the success rate. This classification is in our experiments carried out for each transmitted packet (i.e. an observer performs the classification either after receiving a beacon or after figuring out with the help of a timer that a beacon has just been lost).

Regarding the classification as "lost" (i.e. ∞) we have adopted a simple approach: An observer node diagnoses the mobile node with ∞ when it has not received any beacon packets for a pre-determined amount of time. In our evaluations, we have set the timeout value to the time required to transmit ten beacons.

Based on the observation that our problem of classifying current average RSSI, LQI or success rate estimates into one of a few distinct distances will have to deal with noisy input data, we have adopted an artificial neural network (ANN) as a main vehicle to perform the classification [7, Chap. 4]. ANNs are widely used for classifying noise input data, one application is for example recognition of handwritings.

Our approach works as follows. Suppose that $\{d_1, d_2, \ldots, d_m\} \subset \{5, 10, 15, \ldots, 50, 55\}$ are the distances into which we want to classify the current RSSI/LQI/success rate estimates. For a fixed observer k we have selected k's observations for the first 500 transmitted beacons at distance d_i, which amounts to ten percent of our data – the remaining 90% of our data have later on be used for evaluating classification performance. For each k and d_i we have computed the sample averages for LQI, RSSI and success rate ($E[L_{k,i}]$, $E[R_{k,i}]$ and $E[S_{k,i}]$) for the training data. With seven observers, we get seven triples of sample averages and these seven triples serve as training data for the ANN. The overall ANN training data contains the triples for all distances d_i. It has the following structure: For every distance d_i and every observer node k one point of the training data is given by its input $\{E[L_{k,i}], E[R_{k,i}], E[S_{k,i}]\}$ (actually, scaled versions of these) and the unit vector e_i. We have trained a simple layered feedforward ANN with sigmoid neurons using the backpropagation algorithm [7, Chap. 4], please consult the report [3] for the details. We have experimented with different numbers of layers for the ANN. The number of input nodes is three, since the input is given by the preprocessed averages $\{E[L_{k,i}], E[R_{k,i}], E[S_{k,i}]\}$), the number of output nodes is given by m, i.e. the cardinality of the set of distances into which to classify.

After having trained the ANN, the obtained weights are then used to construct a feedforward ANN. In practice, this feedforward ANN would have to be disseminated to all observer nodes and used by them locally to perform classification. For each packet transmitted by the sender (whether received by k or not), node k would update its statistics (current average RSSI estimate, etc., see Section III-A), apply the chosen subset of the statistics as input to the trained ANN and compute the ANN output (as a simple feedforward calculation). The ANN output is then checked:

- When the difference of the values of the largest and the second-largest output nodes (we interpret this difference as a confidence with which the ANN believes in the winning class as compared to all other classes, consequently we refer to this difference henceforth as the *confidence* of the decision) is larger than a pre-specified threshold, then the distance value corresponding to the output node having the largest value is chosen as the classification result. For this study we have chosen the threshold value as 0.8.
- Otherwise the classification result is undecided, i.e. the classificator outputs the label U.

For the purposes of this study the ANN evaluations have been done offline for each node separately. It must be noted that our requirement of having a threshold value of 0.8 only makes sense when the input data for the classification indeed comes from the chosen distances. For arbitrary input data the classification has to be modified, for example: when the two outputs having the largest magnitude belongs to two neighbored distances d_i, d_{i+1} in the set, then it is plausible to assume that the mobile is "somewhere between d_i and d_{i+1}".

C. Cooperation step

In order to cooperate, observer nodes can either exchange their classification results or the output vector of their local ANN's. Exploiting a loose analogy to decoding algorithms for error-correcting codes, we refer to the exchange of classification results as *hard-decision cooperation* and to the exchange of ANN output vectors as *soft-decision cooperation*.

For this study we have not implemented any protocol to let the observer nodes exchange their observations, but the cooperation step is also performed offline to eliminate the effects of channel contention and observation losses. For the hard decision cooperation procedure we have adopted the following voting rules: (i) The voting result is ∞ only when *all* observers vote ∞. (ii) The voting result is undecided, i.e. U, when at least one node votes U and all other nodes vote for either U or ∞. (iii) When at least one node votes with a real distance, i.e. with one of $d_1, \ldots, d_m$, then the real distance having the most votes is taken. If different distances have the same maximum number of votes, the smallest distance among them is taken. For the soft decision cooperation procedure the rules are: (i) The voting result is ∞ only when *all* observers vote ∞. (ii) Otherwise, the ANN output vectors of all observer nodes not outputting ∞ are summed up. The voted distance is then determined as the distance having the largest sum vector entry.

IV. Experimental performance evaluation

In this section we present the results of a performance evaluation study. We first explain the varied parameters, then the major performance measures and finally some results are presented and discussed. A more comprehensive presentation of results can be found in the technical report [3].

A. Varied parameters

In this paper we consider three different parameters: The number m and the actual set $\{d_1, d_2, \ldots, d_m\} \subset \{5, 10, 15, \ldots, 50, 55\}$ of distances (the *reference distances*) into which the nodes should classify their observations, the number of layers of the ANN, and the mode of cooperation (hard-decision vs. soft-decision). We have used the following reference distance sets: $D_{2,1} = \{5, 30\}$, $D_{2,2} = \{5, 40\}$, $D_{3,1} = \{5, 25, 40\}$, $D_{3,2} = \{5, 30, 55\}$, and $D_{11} = \{5, 10, 15, \ldots, 50, 55\}$. Please note that the first subscript parameter of $D_{m,k}$ refers to the number of distances included in the set, the second simply numbers different distance sets for

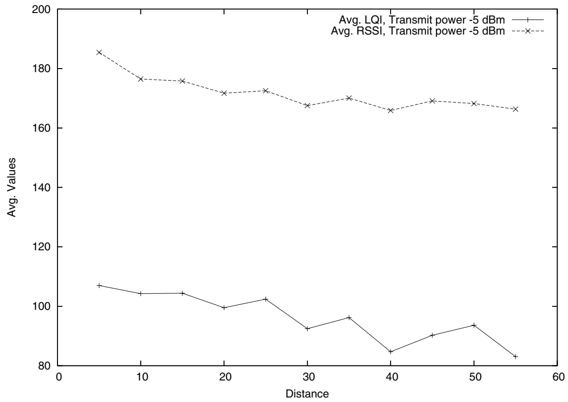

Fig. 1: Average LQI and RSSI values versus distance of transmitter node to the receivers for -5 dBm transmit power

the same m. The distance sets (except D_{11}) have been chosen so that the differences in average LQI and average RSSI for these differences are reasonably large (compare Figure 1).

With respect to the structure of the ANN, we consider two different cases: ANNs with two and with three layers. The ANN consists of at least two layers: the first one is the input layer, which consists of as many input neurons as the number of included statistics, i.e. three. The output layer has exactly m neurons when distance set $D_{m,k}$ is chosen. When a third layer is present, it is a hidden layer. When $D_{2,j}$ or $D_{3,j}$ has been chosen as the distance set, then the number of hidden nodes has been chosen the same as the number of input nodes. When D_{11} has been chosen as the distance set, then the number of hidden nodes is eight.

B. Performance measures

When the mobile node X is at actual distance AD $= d$, the relative frequency by which the (cooperative) classification gives an estimated distance ED $= d$ as well shall be maximized. We refer to this relative frequency with some abuse of notation as

$$\Pr\left[\mathrm{ED} = d \middle| \mathrm{AD} = d\right]$$

and call this, with reference to the theorem of Bayes, the *likelihood*. A large value for the likelihood is beneficial, since it can reduce the number of occasions where node A thinks that X is missing while in truth it is still there, triggering an unnecessary and energetically expensive network-wide search for X in our herding application.

Vice versa, when the classification gives estimated distance ED $= d$, the relative frequency by which the mobile can indeed be found at actual distance AD $= d$ shall be maximized. We call this the *posterior* and write this as

$$\Pr\left[\mathrm{AD} = d \middle| \mathrm{ED} = d\right]$$

The posterior is also very relevant for the envisaged application area: when the system predicts that the mobile is very close and the posterior is close to one, then we can "sleep well" in the "near" state. With a posterior significantly smaller than one we cannot trust our predictions.

Distance	likelihood	posterior	perc. away	perc. undec
5	1.0	1.0	0.0	0.0
40	0.9968882	1.0	0.0	0.0031118025

TABLE I: Likelihood, posterior, percentage of classified packet losses and percentage of packets classified as undecided for a neural network with 2 layers and distance set $D_{2,2}$ (distances (5 40)) (Transmit power is -5 dBm, required certainty is 0.8, hard decision cooperation)

To ease subsequent discussion of the results, we define the following notions for rating the results:

- The results for a particular setting of parameters are rated as *poor* when at least one of the obtained likelihood or posterior values is below 0.9, otherwise they are rated as *good*. While this threshold is somewhat arbitrary, it makes sense to require a classification scheme to perform reliable (i.e. with high probability correct) in the posterior and likelihood sense in order to be useful for a herding system.
- The results are rated as *very poor*, when at least one of the obtained likelihood or posterior values is below 0.1.
- The results are rated as *very good*, when all the obtained likelihood and posterior values are above 0.98.

With respect to methodology, it should be mentioned that the (cooperative) classification results do not cover all the 5000 packets that have been sent by the transmitter node per distance and transmit power, but only those 4500 packets that have not been used for training the ANN. With the trained ANN, each node is fed with his own observations and performs an according classification.

C. Performance results for cooperative classification

We first briefly mention our findings for the distance set D_{11}, in which the observers try to classify the observations into all eleven distances. All results are very poor. When hard decision is involved, sometimes no decision can be achieved, i.e. all nodes classify the mobile at all distances as undecided.

We next consider the distance set $D_{2,1} = \{5, 30\}$, for which we due to lack of space do not show results here (see [3]). For this set all the results are poor, but there is always a classification made, i.e. always at least one node produces a classification having the desired confidence of 0.8.

We show results for the distance set $D_{2,2} = \{5, 40\}$ and a transmit power of -5 dBm in Tables I, II, III, and IV. The results are sometimes very good (Tables I, III), all others are good. The very good ones are hard-decision cooperation schemes with two- and three-layer ANNs, respectively. Furthermore, hard-decision cooperation is consistently better than soft-decision cooperation, although only slightly. There appears to be no appreciable difference between using two- and three-layer ANNs.

Distance	likelihood	posterior	perc. away	perc. undec
5	1.0	0.99733984	0.0	0.0
40	0.9668815	1.0	0.0	0.030451212

TABLE II: Likelihood, posterior, percentage of classified packet losses and percentage of packets classified as undecided for a neural network with 2 layers and distance set $D_{2,2}$ (distances (5 40)) (Transmit power is -5 dBm, required certainty is 0.8, soft decision cooperation)

Distance	likelihood	posterior	perc. away	perc. undec
5	1.0	1.0	0.0	0.0
40	1.0	1.0	0.0	0.0

TABLE III: Likelihood, posterior, percentage of classified packet losses and percentage of packets classified as undecided for a neural network with 3 layers and distance set $D_{2,2}$ (distances (5 40)) (Transmit power is -5 dBm, required certainty is 0.8, hard decision cooperation)

The results for the distance set $D_{3,1} = \{5, 25, 40\}$ are mixed: some are poor, some are good (the ones with soft-decision cooperation) and one is very good (three-layer ANN with hard-decision cooperation). For the distance set $D_{3,2} = \{5, 30, 55\}$ the results are either poor or very poor.

In summary, we can draw the following conclusions from these results. It is possible to classify into two distinct differences with very high reliability (i.e. with both a large likelihood and posterior at the same time) for almost all investigated parameter settings, provided the distances are well chosen. Taking the result shown in Figure 1 into account, it appears to be a good idea to select the candidate distances such that their average LQI and RSSI values differ significantly and, perhaps even more important, the histograms of the LQI / RSSI value observations should overlap as little as possible. For the "good" difference set $D_{2,2} = \{5, 40\}$ this is indeed the case, as is shown in the technical report [3]. The classification into three different distances is only possible for one particular parameter set.

When restricting to the results that are either good or very good, it appears that hard-decision cooperation is preferrable over soft-decision cooperation (it also reduces the bandwidth required for exchanging the results among observers).

Distance	likelihood	posterior	perc. away	perc. undec
5	1.0	0.997561	0.0	0.0
40	0.9671038	1.0	0.0	0.030451212

TABLE IV: Likelihood, posterior, percentage of classified packet losses and percentage of packets classified as undecided for a neural network with 3 layers and distance set $D_{2,2}$ (distances (5 40)) (Transmit power is -5 dBm, required certainty is 0.8, soft decision cooperation)

The larger transmit power of -5 dBm gives many good results for the distance set $D_{2,2}$ and occasionally for the distance set $D_{3,1}$, whereas for the smaller transmit power of -7 dBm good results are only achievable for $D_{2,2}$. This suggests the conclusion that larger transmit powers enable a higher resolution of the number of distances into which to classify.

D. Comparison of cooperation with individual node decisions

The results discussed so far concern only the cooperative classification. It is also interesting to compare the results of the cooperative classification with the results achieved by individual nodes before cooperation. For the sake of space and of relevance, we restrict the comparison to those cases where the cooperation gave very good results.

Dist.	Decider	likelihood	posterior	away	undec	misclass
5	hard-coop	1.000	1.000	.000	.000	.000
5	soft-coop	1.000	.998	.000	.000	.000
5	node 1	1.000	1.000	.000	.000	.000
5	node 2	1.000	1.000	.000	.000	.000
5	node 3	1.000	1.000	.000	.000	.000
5	node 4	1.000	1.000	.000	.000	.000
5	node 5	1.000	1.000	.000	.000	.000
5	node 6	1.000	1.000	.000	.000	.000
5	node 7	1.000	1.000	.000	.000	.000
40	hard-coop	1.000	1.000	.000	.000	.000
40	soft-coop	.967	.998	.000	.030	.002
40	node 1	.526	1.000	.454	.020	.000
40	node 2	.440	1.000	.560	.000	.000
40	node 3	.101	1.000	.899	.000	.000
40	node 4	.859	1.000	.033	.109	.000
40	node 5	.789	1.000	.082	.129	.000
40	node 6	.243	1.000	.756	.001	.000
40	node 7	.752	1.000	.233	.014	.000

TABLE V: Likelihood, posterior, perc. of classified packet losses and perc. of packets classified as undecided for a neural network with three layers, distance set $D_{2,2}$ (distances (5 40)). Transmit power is -5 dBm, required certainty is 0.8.

In Table V we compare for the distance set $D_{2,2} = \{5, 40\}$, a transmit power of -5 dBm and a three-layer ANN (see also Tables III for hard-decision cooperation and IV for soft-decision cooperation) the results of the cooperative classifications with the classifications made by individual nodes before cooperation. Please note that one additional column has been added: the column "misclass." gives the relative frequency of true mis-classifications, i.e. those cases where the mobile node issues packets at distance d_i and the classification yields another distance d_j which is neither ∞ nor U. For 5m distance all individual nodes and the hard-decision cooperation scheme behave similarly, the slightly decreased posterior of the soft-decision cooperation scheme is negligible. For 40m distance the situation is different. The posteriors are all perfect, only the soft-decision cooperation scheme has again slight losses. The likelihood of the individual nodes, however, is in general significantly below the likelihood achieved with the cooperative classification schemes. This loss in likelihood can for all nodes be fully attributed to classifying the node as away (∞, column "away" in Table V) or undecided (U, column "undec" in the table).

Dist.	Decider	likelihood	posterior	away	undec	misclass
5	hard-coop	1.000	1.000	.000	.000	.000
5	soft-coop	1.000	.794	.000	.000	.000
5	node 1	.051	1.000	.000	.949	.000
5	node 2	1.000	1.000	.000	.000	.000
5	node 3	.006	1.000	.000	.994	.000
5	node 4	1.000	1.000	.000	.000	.000
5	node 5	.179	1.000	.000	.821	.000
5	node 6	1.000	1.000	.000	.000	.000
5	node 7	1.000	1.000	.000	.000	.000
30	hard-coop	.184	1.000	.000	.413	.404
30	soft-coop	.367	.794	.000	.004	.629
30	node 1	.022	1.000	.290	.535	.153
30	node 2	.038	1.000	.742	.169	.051
30	node 3	.024	1.000	.590	.356	.030
30	node 4	.041	1.000	.203	.668	.088
30	node 5	.020	1.000	.015	.922	.042
30	node 6	.017	1.000	.092	.746	.145
30	node 7	.061	1.000	.248	.620	.071
55	hard-coop	.948	.980	.000	.048	.004
55	soft-coop	.936	.984	.000	.041	.023
55	node 1	.024	1.000	.963	.012	.000
55	node 2	.687	.972	.113	.199	.001
55	node 3	.030	1.000	.908	.062	.000
55	node 4	.344	.974	.244	.411	.001
55	node 5	.025	1.000	.934	.040	.000
55	node 6	.482	.789	.362	.152	.004
55	node 7	.455	1.000	.039	.506	.000

TABLE VI: Likelihood, posterior, perc. of classified packet losses and perc. of packets classified as undecided for a neural network with three layers, distance set $D_{3,2}$ (distances (5 30 55)). Transmit power is -5 dBm, required certainty is 0.8.

We now look at a less perfect example. We consider the distance set $D_{3,2} = \{5, 30, 55\}$ at a transmit power of -5 dBm and a two-layer ANN, see Table VI for the results. For the distance of 5m all the losses that individual nodes have in terms of likelihood can be fully explained by having the nodes classify the mobile as undecided (U). For the distance of 30m the situation is different: the losses in the likelihood of individual nodes are for no node fully compensated by classifications as U or ∞, but instead individual nodes deliver true mis-classifications. Interestingly, the cooperative schemes give the best likelihoods (with the soft-decision scheme having twice the likelihood than the hard-decision scheme), but at the same time they also have by far the highest rates of mis-classifications. Cooperation can help to correct situations where a node classifies the mobile as ∞, but at the same time cooperation produces more mis-classifications than any individual node does. For the distance of 55m both the cooperative as well as the individual node classifications deliver negligible mis-classification rates, but again the individual nodes often create ∞ classifications which are corrected by cooperation. The cooperative schemes produce also superior likelihoods over the individual nodes. Furthermore, it can be noted that the cooperative schemes do not create better posteriors than the individual node classifications.

V. Conclusions

As one of the key components of a herding system we have identified the determination of the distance between neighbored nodes. To avoid the notoriously hard task of precise ranging, we have instead considered the problem of (cooperative) classification into a few pre-defined distances. Our results indicate that this is possible with high quality in terms of likelihoods and posteriors, but there are limitations. The biggest influence on the achievability of good-quality classification has the size and the values included in the distance set – the best results are achieved for two distances with large separation in their average LQI and RSSI values and very little overlap in the respective LQI / RSSI histograms. It is a possible subject of future work to compare for this distance set the ANN-based classification scheme against simpler classification schemes.

When it comes to judging the gains achievable through cooperation it is important to note that cooperation does not improve on all quality measures. It certainly helps to reduce the rate where the mobile node is classified as "away" (i.e. ∞) and it also increases the likelihood, i.e. of giving the right estimated distance. At the same time, however, cooperation also increases the rate of mis-classifications as compared to the classifications made by individual nodes before the cooperation. It remains to be assessed how other classification schemes would behave here.

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