Activity recognition with implicit context classification

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***Abstract*—We exploit activity recognition from RF-channels. Exceeding current studies, we discuss an implicit recognition scheme to compute context classifications with a network of wireless nodes. In particular, we propose a networked ad-hoc classification scheme that utilises the RF-features on the wireless channel among nodes as implicit inputs. Furthermore, we discuss the possibility to execute mathematical operations during transmission on the wireless channel. We present a data encoding which can be utilised to implicitly add, multiply, subtract or divide values during simultaneous transmission. In a simulation, we demonstrate the computation with a set of values by these implicit operations during transmission.**

***Index Terms*—In-network computation, Wireless communication, Cooperative systems, Pattern recognition, Pervasive computing, Statistical distributions, RF signals**

I. INTRODUCTION

RECENTLY, we have seen several authors utilising the RF-channel for location or activity recognition [1], [2]. In these studies, amplitude-based features, extracted from a received RF-signal are analysed for characteristic patterns to detect the location or activity of a non-actively transmitting entity. Basically, the characteristic fluctuation of the signal's Received Signal Strength Indicator (RSSI), induced by specific activities or by a person located at a distinct position are exploited.

In current studies, the signals have been frequently analysed by Software Defined Radio (SDR) devices and are then classified by a centralised node. However, the greatest potential of device-free RF-based recognition lies in the application by resource-restricted nodes. These can then be turned into sensing devices without requiring additional hardware apart from a commonly anyway available RF-transceiver. With the approaching Internet of Things (IoT), imagine an environment enriched by resource restricted wireless nodes or also by passive tags. With RF-based activity recognition and localisation, such environment holds the potential to evolve to a smart space, monitoring and reacting to the environmental context. However, the strict resource restriction of the devices then likely demands a cooperative context classification rather than the currently frequently employed centralised RF-sensing approach.

After discussing Device-free RF-based sensing in section II, we propose an implicit structure for cooperative context classification in networks of cooperating nodes in section III. Section IV then introduces the concept of mathematical computation during simultaneous transmission to trade computational load in such networks for communication load. Such computations might be utilised for aggregation and calculation of features from a set of data. In particular, we discuss the feasibility to implement basic mathematical operations, as well as typical features from a set of values. The fluctuation of the mean RSSI is, for instance, utilised in Device-free passive sensing approaches for the recognition of locations or activities. Section V presents results from Matlab-based simulations regarding the error experienced for these operations. Section VI finally closes our discussion.

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II. RF-CHANNEL BASED CONTEXT RECOGNITION

Radio waves are electromagnetic waves whose physical attributes are defined by the amplitude, phase offset and frequency. Assume a signal observed at a receiver, at some frequency f_c [Hz]. During signal propagation the energy transmitted by a sender is spread roughly equal in all directions. In the event that a radio wave encounters any concrete structure such as an object or individual, it will be damped (continue its path with reduced energy) or even completely blocked. Additionally, the signal is typically reflected or scattered at this event. Reflection expresses the event that the signal wave bounces away from an object in an altered direction. Scattering denotes the splitting of a signal wave into several waves due to the not perfectly even structure of the object and the propagation of these signal waves into diverse directions from the object. The propagation speed of electromagnetic waves can be approximated with the speed of light $c = 3 \cdot 10^8 \frac{m}{s}$ and is identical for all signal components. Consequently, signal components with longer signal propagation paths arrive later at a receiver. The received signal

$$\zeta_{\text{rec}} = \Re\left(m(t)e^{j2\pi f_c t}\sum_{i=1}^{n}\text{RSS}_i e^{j\gamma_i}\right) \tag{1}$$

is composed of distinct signal components along various signal paths between a transmitter and a receiver. In equation (1) the RSS_i denotes the received signal strength of the i-th signal out of n received signal components. The value γ_i accounts for the phase offset in the received signal components due distinct signal propagation times and offsets in local oscillators. Due to signal reflection at objects, a change in the environment such as the presence of persons or changed location of objects will result in differing signal propagation paths between a transmitter and a receiver. Such a change might then alter the signal strength at the receiver and also the phase of

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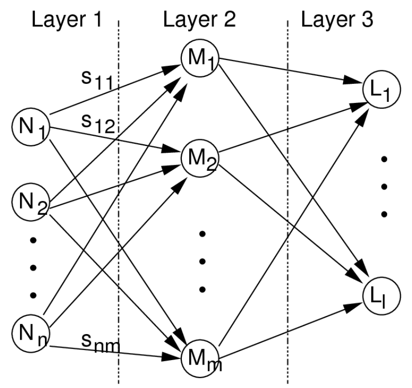

Fig. 1. Schematic illustration of a context classification network

the signal $\zeta_{\text{rec}}(t)$. Furthermore, the noise figure ζ_{noise} might change depending on the environment.

The classification of locations, activities and situations of non-actively transmitting entities based on ambient RF-signals was recently considered by several research groups. Results are typically achieved by analysing the RF-signal amplitude, namely the RSSI of a received signal.

Youssef et al. for instance, exchanged packets between 802.11b nodes in corners of a room and analysed the moving average and its variance of the RSSI [3], [4]. Woyach et al. investigated effects due to line of sight (LOS) obstruction or multipath fading on the Received Signal Strength (RSS) of a RF-channel to localise passive objects in-between nodes [5]. Zhang et al. used 870 MHz WSN nodes arranged in a grid to show that for each link an elliptical area exists for which RSSI fluctuation caused by an object traversing this area exceeds measurements in a static environment [6]. An object could be localised with an accuracy of about 1m [7]. Wilson and Patwari demonstrated good localisation and tracking results by tomographic imaging and used the two-way RSSI variance [8] or RSSI mean fluctuation [9] between nodes arranged in a rectangle surrounding the monitored area [10]. They also showed the robust localisation of two people simultaneously and introduced a statistical model to approximate the position of a person based on RSSI variance [1].

These approaches detect location rather than activity. Recently, also activities could be detected from RF-channel measurements. Patwari et al. monitor breathing from two-way RSSI measurements of 2.4GHz nodes surrounding a lying individual [1]. Also, we conducted preliminary studies regarding the use of features from an RF-transceiver to classify static environmental changes such as opened or closed doors or windows, presence, location and count of persons [11], [2], [12]. It was shown that these environmental situations could be detected with good accuracy in several environments.

III. Implicit in-network classification

For device-free passive RF-based recognition systems, figure 1 sketches a possible topology. One or more transmit nodes in layer 1 emit an RF-signal, which is, after experiencing several RF channel effects, being collected by one or more receive nodes in layer 2. In this model, we distinguish between n input nodes $\mathcal{N}_i, i \in \{1..n\}$, m inner nodes $\mathcal{M}_j, j \in \{1..m\}$ and l output nodes $\mathcal{L}_k, k \in \{1..l\}$. Input nodes $\mathcal{N}_i$ transmit a signal

$$\zeta_i = \Re\left(m(t)P_{\mathcal{N}_i}e^{j2\pi f_i t\gamma_i}\right) \tag{2}$$

at predefined transmit power $P_{\mathcal{N}_i}$ to inner nodes $\mathcal{M}_j$. We denote the feature values experienced for a signal transmitted by node $\mathcal{N}_i$ and received by $\mathcal{M}_j$ as s_{ij}. For combination of data in a third layer, inner nodes $\mathcal{M}_j$ implement a, possibly nonlinear, function $f_{\mathcal{M}_j} : (s_{0j}, \ldots, s_{nj}) \rightarrow \mathbb{R}$ which is activated by a combination of all $s_{ij}, i \in \{0..n\}$. The output of $f_{\mathcal{M}_j}$ then determines the signal transmitted by node $\mathcal{N}_j$. Which then again propagates a wireless channel from $\mathcal{M}_j$ to $\mathcal{L}_k$ and experiences environmental impacts on the channel. At the output node $\mathcal{L}_k$, again a combination of all received values is input to a function $f_{\mathcal{L}_k} : (s_{0k}, \ldots, s_{mk}) \rightarrow \mathbb{R}$. The output of $f_{\mathcal{L}_k}$ defines the output of the computed function and contains implicitly the environmental stimuli. The function which is computed by this graph is described by

$$\begin{aligned} g_k(\overrightarrow{s_{ij}}) &= f_{\mathcal{L}_k}\left(s_{0k}, \ldots, s_{mk}, f_{\mathcal{M}_j}\left(s_{0j}, \ldots, s_{nj}\right)\right); \\ \overrightarrow{s_{ij}} &= \left(s_{0,k}, s_{1k}, \ldots, s_{m,k}, s_{0j}, s_{1j}, \ldots, s_{nj}\right). \end{aligned} \tag{3}$$

In equation (3), s_{0j} and s_{0k} denote additional weights that can be adapted to realise a specific function. When we define $s_{ij} = s'_{ij} \cdot x_i$ and assume that the functions $f_{\mathcal{M}_j}$ and $f_{\mathcal{L}_k}$ implement a non-linear function on the sum of their inputs, we obtain

$$f_{\mathcal{L}_k}\left(\sum_{j=1}^{m} s_{jk} \cdot f_{\mathcal{M}_j}\left(\sum_{i=1}^{n} s'_{ij} \cdot x_i + s_{0j}\right) + s_{0k}\right) \tag{4}$$

for the network structure depicted in figure 1, which (with input $\overrightarrow{x}$) is the definition of a three-layer perceptron neural network [13], [14], [15].

Consequently, equation (4) can describe arbitrary non-linear functions, provided that the count m of nodes $\mathcal{M}_j$ in the hidden layer is sufficiently high [13]. The expressive power of both models is identical. The difference to neural networks is that not the x_i are considered as environmental input but the values s_{ij} which fluctuate with environmental changes. The x_i instead are static and are provided by the input nodes $\mathcal{N}_i$ constantly. We propose this structure for implicit RF-based context classification networks. After installation in an environment, identical input features (induced by specific situations) will always translate to identical output values.

IV. Mathematical operations during transmission

In the previous section we introduced a structure for implicit in-network context classification. This structure is capable to distinguish different environmental situations with different output values. In context classification, however, features are not always directly extractable from context data but frequently have to be computed first. We discuss in this section how such operations are possible based on features observed on the RF-channel of a wireless network. In particular, we show how values can be added or multiplied on the wireless channel at the time of simultaneous transmission. We also discuss the computation of subtraction or division during transmission. With these operations, it is then for instance possible to calculate the mean of a set of values, a feature frequently utilised for RF-based context classification.

We assume that a set of weakly synchronised, distributed wireless nodes $\mathcal{N}_1, \ldots, \mathcal{N}_n$, each holding a value $v_i; i \in \{1, \ldots, n\}$ is to combine their values v_i during transmission by computing a function $f(v_1, \ldots, v_n)$ in a way that a receiver will obtain the result of the computation $f(v_1, \ldots, v_n)$ rather than the distinct values $v_1, \ldots, v_n$. In order to achieve this, we propose to use probability distributions and the algebra of random numbers [16]. We represent the values v_i as the mean of a Poisson distribution and encode this distribution sufficiently so that no exact synchronisation among nodes is required and superimposition of representations result in a representation that encodes the result of the function $f(\cdot)$.

For an interval of length t, divided into κt sub-intervals of length $\frac{1}{\kappa}$, each with probability p_κ that it contains one or more of a finite number of points, the Poisson distribution [17] is defined as the probability of finding exactly k points in this interval:

$$p(k; \mu t) = e^{-\mu t} \frac{(\mu t)^k}{k!} \quad (5)$$

The parameter μ is a physical constant which determines the density of points on the t-axis. The larger μ is, the smaller the probability of finding no point. It is also the mean of the distribution. For two Poisson distributed variables χ_1 and χ_2 with means μ_1 and μ_2, $\chi_1 + \chi_2$ is again a Poisson distributed random variable with mean $\mu_1 + \mu_2$ [16].

We utilise this property to realise addition and multiplication during transmission on the wireless channel. Instead of classical transmission protocols we employ burst sequences that constitute a sequence of possible transmit intervals $\mathcal{TI}$ of predefined length. In each of these intervals, a transmitter will either be silent or transmit a burst. We define a transmission sequence of t transmit intervals $\mathcal{TI}$ and divide this into κt sub-intervals of length $\frac{1}{\kappa}$. To transmit a value v_i we define a Poisson process with $\mu = v_i$. The transmit sequence is then designed such that each of the sub-intervals has the probability p_κ that it contains one or more of a finite number of bursts. The probability of finding exactly k bursts in a fixed interval of length t is then again

$$p(k; \mu t) = e^{-\mu t} \frac{(\mu t)^k}{k!} \quad (6)$$

To observe the value μ at a receiver, we extract values N_i with N_i denoting the count of sub-sequences with exactly i bursts.

$$N_0 + N_1 + N_2 + \ldots = N \quad (7)$$

Also, the total number of bursts is

$$N_1 + 2N_2 + 3N_3 + \ldots = T. \quad (8)$$

If N is large, we expect that [17]

$$N_k \approx N p(k; \mu t) \quad (9)$$

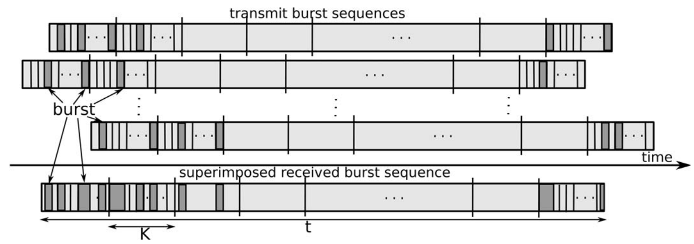

Fig. 2. Superimposition of burst sequences for computation on the wireless channel

Substituting equation (8) and equation (9) we find

$$\begin{aligned} T &\approx N\left(p(1; \mu t) + 2p(2; \mu t) + \ldots\right) \\ &= N e^{-\mu t} \mu t \left(1 + \frac{\mu t}{1} + \frac{(\mu t)^2)}{2!} + \ldots\right) \\ &= N \mu t \end{aligned} \quad (10)$$

and hence

$$\mu t \approx \frac{T}{N}. \quad (11)$$

A receiver can therefore extract the value μ from a transmission. Of course, this process is exhaustive to transmit a single value. However, it can also be used to combine several values transmitted simultaneously, thereby computing $\sum_{i=1}^{n} \mu_i$ as depicted in figure 2. The figure illustrates schematically the superimposition of burst sequences. In particular, observe that burst sequences are not required to be exactly aligned. Since in each sub-sequence the same probability applies to uniformly distribute a number of bursts, a relative shift of the burst sequences does not change the overall probability in the superimposed sequence. Errors are merely induced at the beginning or end of the sum-sequence but these are negligible when t and κ are sufficiently large.

When several sequences are transmitted simultaneously, the superimposed sequence at the receiver contains the bursts of the original sequences. This includes the possible case of two bursts being transmitted at the same time, which will induce a small error.

Observe that equation (7) and equation (8) require addition on their own. However, since this is a monotonic operation, it could be implemented in the transceiver module in hardware and does then not induce computational load at the receiver. Provided that the burst sequence is sufficiently sparse, this can be scaled to an arbitrary number of signals transmitted simultaneously. The computational complexity at the receiver remains the same regardless of the count of sequences combined, increasing efficiency with increasing count of participants.

A similar model can also be used for multiplication on the wireless channel. Since

$$\log_a(X) + \log_a(Y) = \log_a(X \cdot Y). \quad (12)$$

$$a^X \cdot a^Y = a^{X+Y}. \quad (13)$$

we can achieve multiplication of $v_i, i \in \{1..n\}$ on the wireless channel in the same way by using equation (12).

$$\sum_{i=1}^{n} \log(x_i) = \log\left(\prod_{i=1}^{n} x_i\right) \quad (14)$$

In the same manner we can also realise division and subtraction on the wireless channel. From equation (11) we see that the mean value is divided by a when N is divided by a. The values t and T need not be modified. For a quotient

$$\overline{\mu} = \frac{\mu}{a} = \frac{T}{N \cdot t \cdot a} \tag{15}$$

we have to provide a dividend μ and a divisor a. We require that the dividend T and the divisor $t \cdot N$ are fixed. This is a sharp restriction since then the components to compute μ are required at the node transmitting the divisor. However, for resource limited nodes, this might still enable complex operations not possible otherwise. For instance, consider a sequence of mathematical operations on the channel, in which several nodes might have observed the result of a previous operation so that the required information is implicitly available and division can be executed without computational effort.

We consider the case of two nodes, one transmitting the divisor and one the dividend. Assume the dividend to be

$$\mu = \frac{T}{t \cdot N} \tag{16}$$

This value is encoded by a burst sequence as detailed above. Now, to divide this value by a divisor a, the node responsible for the divisor will transmit a sequence with

$$\begin{aligned} T' &= T, & (17)\\ t' &= t, & (18)\\ N' &= 2Na - N. & (19) \end{aligned}$$

In the optimum case that no collisions occur, the resulting sequence is then characterised by

$$\begin{aligned} \overline{T} &= T' + T = 2T, & (20)\\ \bar{t} &= t, & (21)\\ \overline{N} &= N' + N & \\ &= N + 2Na - N = 2Na. & (22) \end{aligned}$$

Consequently, we obtain $\overline{\mu}$ as

$$\overline{\mu} = \frac{2T}{t \cdot 2Na} = \frac{T}{tNa} = \frac{\mu}{a}. \tag{23}$$

Again, with logarithm rules we can realise subtraction.

Typical operations used to calculated features from RF-channel characteristics are, for instance, the mean $\hat{\mu}$, the standard deviation σ, the Root of the Mean Square (RMS) or the Average Magnitude Squared (AMS) [11]:

$$\begin{aligned} \hat{\mu} &= \frac{\sum_{t=1}^{n} |\zeta_{\text{rec}}(t)|}{n} & (24)\\ \sigma &= \sqrt{\frac{\sum_{i=1}^{n}(v_i - \mu)^2}{n}} & (25)\\ \text{AMS} &= \left(\frac{\sum_{t=1}^{n} \zeta_{\text{rec}}(t)}{n}\right)^2. & (26)\\ \text{RMS} &= \sqrt{\frac{\sum_{t=1}^{n}(|\zeta_{\text{rec}}(t)| - \mu)^2}{n}}. & (27) \end{aligned}$$

With the operations defined, the mean μ of a set of values can be exclusively computed on the wireless channel as illustrated in figure 3. In the scheme detailed in the figure, a set of nodes

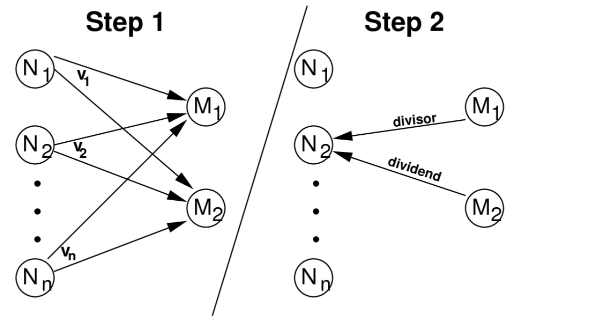

Fig. 3. Calculation of the mean of a set of n values exclusively on the wireless channel

$\mathcal{N}_1 \ldots \mathcal{N}_n$ first simultaneously transmits n values to add them at a receive node. The superimposition is observed by two nodes M_1 and M_2 that in turn transmit the divisor and the dividend to compute

$$\hat{\mu} = \frac{\sum_{i=1}^{n} v_i}{n} \tag{28}$$

as described above.

All other features can only partly be offloaded to the channel since they require the operation of the square-root or square. We have currently not found a simple way to compute these features on the wireless channel in a single step. However, still a significant share of the overall computational load can be offloaded to the wireless channel also for these features.

V. Simulations

We conducted matlab-based simulations to estimate the error induced by applying computations on the channel. In particular, we distributed 10 to 50 nodes uniformly at random on a $30m \times 30m$ square area. The receiver is located 3 meters or 10 meters above the centre of this area. We calculate the phase offset of the received dominant signal component from each transmitter according to the transmission distance in a direct line of sight. For a signal wavelength λ and a transmission power of P_{tx} over a distance d, path loss was calculated by the Friis free space equation $P_{tx}\left(\frac{\lambda}{2\pi d}\right)^2 G_{tx}G_{rx}$ with antenna gain for transmitter and receiver as $G_{rx} = G_{tx} = 0$ dB. Burst signals $m_i(t)$ are transmitted at 2.4 GHz with transmit power $P_{tx} = 1$ mW. All received signal components calculated in this manner are then summed up in order to achieve the superimposed sum signal

$$\zeta_{\text{sum}}(t) = \sum_{i=1}^{n}\left(\Re\left(m_i(t)\text{RSS}_i e^{j(2\pi(f_c)t + \gamma_i + \phi_i)}\right)\right). \tag{29}$$

In equation (29), γ_i and ϕ_i denote the relative phase offset at transmitter i and the additional offset induced by the signal propagation. Finally, a noise signal $\zeta_{\text{noise}}(t)$ is added to $\zeta_{\text{sum}}(t)$ in order to estimate the signal at the receiver. We utilise AWGN at -103 dBm as proposed in [18]. For a given configuration we repeated each simulation 10 times with identical parameters.

Figure 4 depicts a received, superimposed sum signal from 10 transmit nodes with a distance of 10 meters between the

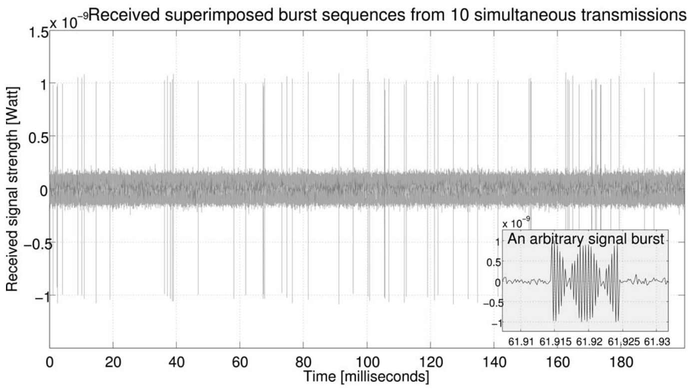

Fig. 4. A superimposed burst sequence from 10 distinct transmit nodes and an enlarged view on an arbitrary signal burst

TABLE I
ERRORS EXPERIENCED BY CALCULATION OF VALUED DURING SIMULTANEOUS TRANSMISSION ($t = 10^6$ AND $\kappa = 10^3$)

	10 nodes	20 nodes	30 nodes	40 nodes	50 nodes
median err	0.02305	0.0402	0.03285	0.0458	0.0658
mean err	0.322	0.0466	0.0609	0.051	0.0719
std-dev.	0.0232	0.0368	0.0536	0.0336	0.0438
max N_i	9	14	18.5	26	31
median T	2653.5	5161.5	7393	101816	124179

receiver and the center of the field. We observe that bursts are clearly distinguishable from the background noise and are randomly distributed over the whole transmission window. In the simulations, each node draws a value for μ randomly from $[0, 0.5]$ and creates the burst transmit sequence accordingly. Afterwards, these sequences were simultaneously transmitted. Due to the weak synchronisation among nodes and the distinct signal propagation times, the sequences are not synchronised at the receiver node. The receiver then counts the bursts and estimates the resulting $\overline{\mu}$ value as a result of the computation.

Table I depicts our results for network sizes of 10 to 30 nodes, $t = 10^6$ and $\kappa = 10^3$. We observe that the median error for this configuration of the transmit sequence is stable also with increasing count of participating nodes. However, the maximum value for all N_i increases with increasing node count, as more bursts are contained in each sub-sequence. Consequently, also the probability for collisions increases. With 40 nodes that transmit simultaneously, we observed already a maximum N_i value of 24. The error in this case moderately increases to 0.0336.

Summarising, although the error observed for the calculation is not negligible with about 0.03 while values for μ are drawn from the interval $[0, 0.5]$, simple computations, combining a great number of transmit nodes, are possible with a rough error correction. By increasing the count of sub-intervals by either increasing t or decreasing the burst length, the error can be arbitrarily decreased at the cost of simultaneously increasing the transmission time. For the configuration utilised in the simulations, the transmission time with $t = 10^6$ at 2.4GHz is about 10 milliseconds with a burst length of 0.01μseconds. We exemplary increased the count of sub-sequences to $t = 10^7$ (100ms transmission time). Table II shows that the accuracy is greatly improved then.

TABLE II
ERRORS EXPERIENCED BY CALCULATION OF VALUED DURING SIMULTANEOUS TRANSMISSION ($t = 10^7$ AND $\kappa = 10^3$)

	10 nodes	20 nodes	30 nodes	40 nodes	50 nodes
median err	0.002	0.0187	0.0467	0.0534	0.0858
mean err	0.0049	0.0176	0.0402	0.0475	0.0781
std-dev.	0.0062	0.0127	0.0233	0.0292	0.0405
max N_i	12	18	23	27	31
median T	25708.5	52617.5	78502	101381	114348

TABLE III
ERRORS EXPERIENCED BY CALCULATION OF VALUED DURING SIMULTANEOUS TRANSMISSION ($t = 10^7$ AND $\kappa = 10^2$)

	10 nodes	20 nodes	30 nodes	40 nodes	50 nodes
median err	0.0211	0.12965	0.2536	0.4672	0.6448
mean err	0.0190	0.1337	0.2619	0.4903	0.6597
std-dev.	0.0107	0.0358	0.0591	0.0708	0.1129
max N_i	9.5	16	19	24	27
median T	24165	50037	71686.5	96829	114383

When instead the sub-sequence length is reduced to 100 (1ms transmission time), the accuracy is impaired as depicted in table III. We observe that the error experienced is in the same order as above for the situation with 10 nodes. However, when the number of participating nodes increases and consequently the probability for collisions of transmit bursts, the error quickly increases as expected. Consequently, with this transmission scheme, accuracy increases with transmission time.

VI. CONCLUSION

We have discussed implicit context classification schemes in networks of wireless nodes, passively and actively utilising features obtained from the RF-channel. In particular, we have presented a classification scheme for implicit context classification and demonstrated the execution of mathematical operations on the wireless communication channel by utilising a Poisson distributed process to generate transmission bursts. In a simulation environment, the error of these mathematical operations was exploited.

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