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Model-based Evaluation of Location-based Relaying Policies in a Realistic Mobile Indoor Scenario

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***Abstract*—For WLAN systems in which relaying is used to improve throughput performance, node mobility and information collection delays can have a significant impact on the performance of a relay selection scheme. This paper analyzes this influence on the decision process using a previously developed Markov Chain model. The evaluation is done for a realistic indoor scenario that is based on ray-tracing enriched measurements from the WHERE2 project. Further, these results are compared to results obtained using an idealistic path loss model, and we show that the performance impact of node mobility and information collection delays is significantly different for the two data sets.**

I. Introduction

In WLANs it is well-known that two-hop relaying can improve throughput for some users [1], [2], [3]. However, for such link measurement based approaches as well as location based approaches [4], [5], [6] node movements and information collection delays can negatively impact performance, as shown using a Markov Chain based model in [7]. For this analysis an idealistic distance based path loss model was assumed, which did not model the multi path effects that are present in indoor environments. The present paper addresses this by comparing results obtained with such an idealistic path loss model, to results based on realistic ray tracing enhanced measurements, produced during the WHERE1 and WHERE2 projects. The results are not meant as an exhaustive site-survey but simply as a realistic comparison case.

Section 2 introduces the general relay system, while the corresponding Markov model is described in Section 3. The ray-tracing enhanced measurement based use case study is described in Section 4 and in Section 5 we present a comparison of the results obtained with the idealistic and realistic data sets using the Markov Chain model from [7].

II. System Description

We consider the three node system sketched in Fig. 1, consisting of a static access point (AP), mobile relay R, and static destination D. The candidate relay R has a position $(x_R(t), y_R(t))$ that changes over time. Note that D is static, so dynamic changes result purely from R's mobility. In a location-based relaying approach, the AP in this situation needs to take a decision whether – based on its inaccurate (delayed) knowledge of the position of the candidate relay – relaying is beneficial or not. The mapping of the estimated position of R to the relay decision is called a *relay policy*, here represented by $\pi(\hat{x}_R, \hat{y}_R) \in \{R, D\}$, where R is 'relay' and D is direct transmission. In this paper, we assume that such relay decision is taken just before each individual data fragment transmission.

This scenario could correspond to a use case where a user is located in an office with quite poor wi-fi coverage, where he tries to exploit bypassing colleagues' wireless devices as mobile relays. It should be noted that the proposed modeling approach works equally well for the situation where the relay is static and instead the destination is mobile.

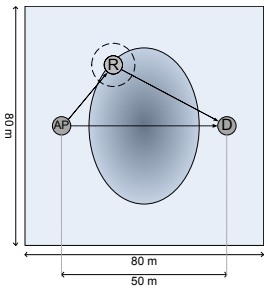

Fig. 1. System with static AP, mobile relay (R), and static destination (D). The gradient ellipse illustrates where relayed transmissions yield higher throughput than direct transmissions. The dashed circle around R is the position uncertainty.

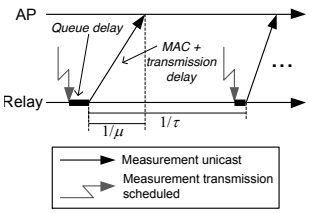

Fig. 2. Location measurements are transmitted periodically with rate τ and are subject to queueing delay as well as MAC and transmission delay. The latter two are represented by a distribution with mean $1/\mu$.

The positions of the static AP and of the destination D are assumed to be known at the AP, hence only the mobile relay node will periodically (with rate τ) send position updates $(\hat{x}_\mathrm{R}, \hat{y}_\mathrm{R})$ to the AP. It is assumed that such location information is available at R through, e.g., a GPS system. In order to investigate the impact of the forwarding delays of positioning information in mobile scenarios, it is assumed that the only cause of inaccurate information is the mobility. Therefore, the position information obtained at R is assumed to be exact.

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The location measurements are transmitted from the relay to the AP, as sketched in Fig. 2: Node R obtains an exact coordinate of its current location, wraps it into a WLAN packet and passes it to its WLAN interface. At the WLAN interface, there could be a queuing delay until the location message reaches the first position in the (finite) interface queue, followed by a subsequent MAC and transmission delay. The sum of MAC and transmission delays are assumed to show a distribution with mean $1/\mu$.

The AP's estimate of Node R's position is based on the last received location measurements. Since the relay is mobile its true position may differ from the AP's estimate, depending on the stochastic mobility model of the candidate relay. For many mobility models, the older the most recent measurement becomes, the less accurate the AP's view is expected to be.

Depending on the AP's belief on the relay's location it will choose to either make a relayed (R) or direct data transmission (D). The resulting throughput will depend on this choice. A throughput increase can be achieved by the choice of a high bit rate coding scheme when the relay to node distances are shorter than the AP to destination distance. However, as we assume decode and forward relaying here, the relayed transmission requires two packets to be sent which will lead to additional channel occupation affecting throughput. For the numerical results later, we utilize the throughput model of [8], which is summarized in Section IV-C.

III. Model for Relaying Performance Assessment

For optimal performance, it is desirable to make the choice that maximizes the overall achieved throughput. In the considered scenario, this optimal choice depends on the node mobility models, on the distant-dependent propagation characteristics, and on the strategy (period of the location updates) and forwarding delays (queuing, MAC and transmission) of these location updates. In this section, we summarize the Markov model we developed in [7] that is later in this paper applied to a realistic indoor scenario.

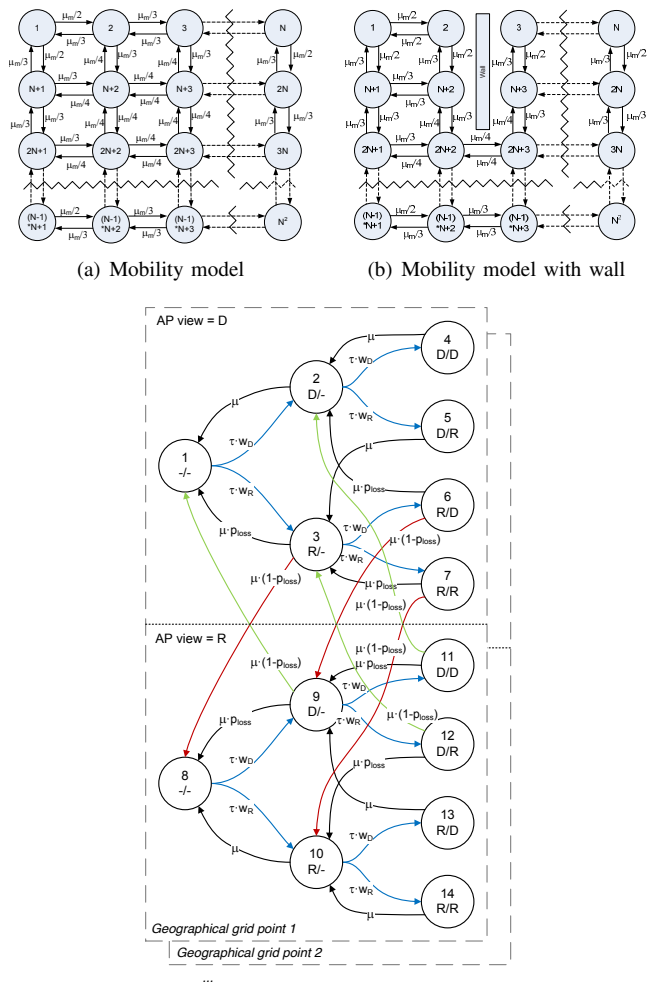
The main approach for the Markov model is to start from a product-space representation of two parts: 1) a continuous time Markov model for the spatial mobility of the candidate relay node (the 'true' coordinates); 2) a model of location update procedures and of the resulting AP view. As these two parts are not completely independent, a pure product space approach however is not sufficient, but requires subsequent modifications as summarized in this section.

Performance metrics are calculated from the steady-state solution of the Markov chain, see [7] for more details.

Markov Mobility Model

First element of the relaying Markov model is a continuous time Markov model that describes the candidate relay's stochastic mobility. The geographic 2-dimensional space is discretized, for instance via a equidistant grid. The states then represent the current true position of the candidate relay within the grid. Transition rates between the states characterize the mobility. Fig. 3(a) shows a base model without obstacles as it was used in [7]: Transitions are only allowed to the neighboring grid states and all states have the same overall state leaving rate μ_{m}. As a consequence, the average movement speed of the candidate relay can be readily obtained as $\bar{v} = d/\mu_m$, where d is the distance between neighboring grid-points.

The example in Fig. 3(a) (b) shows an example mobility model for indoor scenarios in which a wall blocks certain movements. The actual used more complicated setting will be later explained in Figure 5(a).



(a) Mobility model (b) Mobility model with wall

(c) Information forwarding model

Fig. 3. (a) Example Markov mobility model without obstacles or walls. $N \times N$ discrete grid-points represent the geographic space. μ_{m} is the state-leaving rate. (b) A similar mobility model, but with a wall. (c) State overview for Markov model of information forwarding.

AP View and Information Forwarding

In order to model the AP view on the relaying input information and the location update process, the state-space at each coordinate (state of the mobility model) an extended model of each grid point was developed in [7] as shown in Fig. 3(c). The following gives a very brief summary of the model, see [7] for more details. Based on the AP's

current knowledge of the mobile relay's position the AP can apply the relaying policy that maps geographic coordinates to either action, 'D'=Direct Transmission or 'R'=Relay. Instead of keeping the coordinate knowledge in the state-space, the Markov model just tracks the current decision resulting from the policy, i.e. in the example direct transmission in States 1-7 or relay transmissions in States 8-14.

Updates on the relay's position are created by the relay node with rate τ, shifting the state to the right in Figure 3(c), indicating one (middle column) or two (right column of states) updates in progress. Depending on whether the policy maps the update in progress to a direct or a relay view, the change will go up (for direct, e.g. 2 to 4) and down (for relay, e.g. 3 to 7). The up or down is determined by the functions w_D and w_R which attains either the value 0 or 1 depending on the grid position and the policy $\pi(m)$. The model in the figure allows for two updates in progress, representing a interface card buffer with room for one update (and one being in progress of transmitted). Subject to the network delay rate μ the update message reaches the AP, which may lead to a change of decision for the AP. Finally, with probability p_{loss} a message may be dropped by the network.

Geographic Throughput Model

In order to calculate expected throughput of the relaying system, we here assume that this expected throughput is only influenced by variability due to mobility. As we here assume that AP and target nodes are static, we only require the candidate node's position as input. The throughput for a the direct transmission is thereby constant, while the relayed cased depends on the location of the relaying node. The specific WLAN 802.11 throughput model from [8] is used in the case study; it will be summarized in Section IV-C.

IV. Measurement based Use Case Study

For demonstrating the application of the proposed model, we consider a case study that reflects the scenario in Fig. 1. AP and D Nodes are static, whereas the R Node moves according to the Markov mobility model presented in Section III. Note that the AP and D positions have been manually selected in order to show a scenario where relaying can be beneficial. For other positions of the AP and D nodes the direct transmission mode is always best, which would result in a valid but very trivial analysis outcome. The Nodes are equipped with 802.11g based radios, but modified to support relaying as mentioned in [4]. Furthermore, since the area is small compared to the typical range of 802.11g the transmission parameters have been scaled down to imitate a scenario in which relaying is usable. Table I lists the used scenario and simulation parameters. The specific scenario is described in the following.

A. Ray Tracing Simulation

PyRay tool, an UWB ray tracing simulator has been used to produces a large set of UWB received signal on a grid of 51 pseudo Access-points $\times$ 363 Mobile Station (MSs) on a uniform grid which cover the same office building where the UWB WHERE1 measurement campaign has been conducted. Those simulated received waveforms have been built in order to reproduce as closely as possible the whole transmission chain including various effects (waveform convolution, Tx and Rx antennas) in order to allow a fair comparison with actual measurement data. For simplicity, this paper only covers the leftmost 2/5 of the building shown in Fig. 4.

Now, given the UWB received signals, in order to evaluate the scenario under the assumption of IEEE 802.11g WiFi, it is necessary to first extract the narrow band path loss from the measurements, and thereafter estimate the achievable throughput from the path loss.

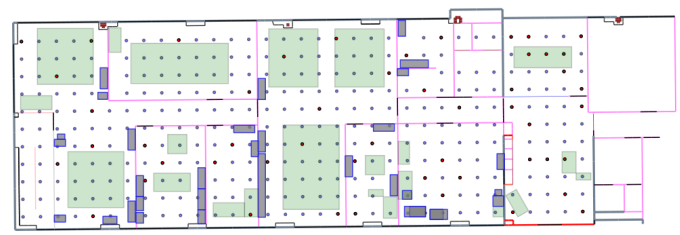


Fig. 4. The indoor Layout with furniture and the used grid of point (pseudo AP and destination nodes are in red.)

B. Evaluating Narrow Band Path Loss from UWB Signal

The UWB waveform $p(t)$ which has been used for simulation is energy normalized and is expressed mathematically as follow:

$$p(t) = \sqrt{\frac{2\sqrt{2}}{T_p\sqrt{\pi}}} e^{-\left(\frac{t}{T_p}\right)^2} cos(2\pi f_c t) \tag{1}$$

with

$$T_p = \frac{2}{B_{-\gamma_{dB}}} \sqrt{\frac{\gamma_{dB}\ln(10)}{20}}, \tag{2}$$

where $f_c = 4.49\,\text{GHz}$, $B_{-3\text{dB}} = 500\,\text{MHz}$, $\gamma_{\text{dB}} = 3$. Thus, what is available, in the database, for each link is the computed convolution product $r(t) = p(t) \star h(t)$ of the UWB waveform $p(t)$ and the CIR of the channel impulse response $h(t)$. In practice this convolution is performed in the frequency domain using the Fourier transform of each quantity $R(f) = P(f)H(f)$.

In order to obtain a location dependent parameter, which is independent of the shape and magnitude of the applied waveform, it is necessary to define a path loss quantity constructed from the UWB received waveform. The used path loss is defined as the energy ratio between the applied and the received signal filtered out in a narrow band of interest which is evaluated as follows:

$$L_{\text{NB}}(f_c, b) = 10\log_{10}\left(\frac{\int_{fc-\frac{b}{2}}^{f_c+\frac{b}{2}} |P(f)|^2 df}{\int_{fc-\frac{b}{2}}^{f_c+\frac{b}{2}} |R(f)|^2 df}\right) \tag{3}$$

For our simulation the value $b = 20\,\text{MHz}$ has been chosen, corresponding to $B = N \times b$ with $N = 25$, and $f_c = 2.412\,\text{GHz}$ corresponding to IEEE 802.11g channel 1. For an extensive description of the ray tracing scenario, see [9].

C. Used Throughput Model

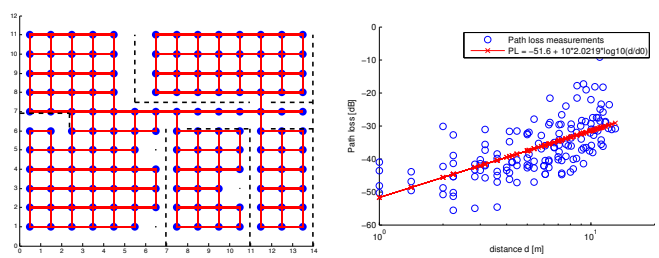
Given the extracted path loss for a narrow band corresponding to IEEE 802.11g channel 1, we estimate the achievable throughput from the path loss. The throughput model of IEEE 802.11 that is used in this paper is based on previous work, further detailed in [8]. As the throughput is given by $\frac{\text{Delivered data}}{\text{Transmission time}}$, and using bit-error-rate models to calculate the frame error probabilities (see [8] for details), the throughput can be calculated as:

$$S_{\text{dir}} = \frac{P_{\text{suc}} \cdot B_{\text{MSDU}}}{E[T_{\text{tx}}]} \tag{4}$$

where P_{suc} is the probability of a successful MAC layer frame delivery, $E[T_{\text{tx}}]$ is the duration of a MAC frame delivery attempt, and B_{MSDU} is the MAC payload size given in octets. In the following, we use the indices 1 and 2 to indicate the AP-r and r-d transmissions. The throughput for the two-hop relaying algorithm is calculated as:

$$S_{\text{rel}} = \frac{(P_{\text{suc}}^{\text{pri},1} P_{\text{suc}}^{\text{pri},2} + P_{\text{suc}}^{\text{sec},1} P_{\text{suc}}^{\text{sec},2}) \cdot B_{\text{MSDU}}}{E[T_{\text{tx}}^{\text{pri},1}] + E[T_{\text{tx}}^{\text{pri},2}] + E[T_{\text{tx}}^{\text{sec},1}] + E[T_{\text{tx}}^{\text{sec},2}]}. \tag{5}$$

The throughput model is used to estimate the transmission throughput functions $T_{\text{D}}(m)$ and $T_{\text{R}}(m)$ for each of the M grid points, indexed by m.



(a) Mobility model (b) Path loss model estimation

Fig. 5. (a) Mobility model in room layout. Red lines are possible movements between states (blue dots) and black dashed lines are walls. (b) Estimation of path loss model parameters, namely reference path loss at 1m and path loss exponent.

V. Model Based Analysis

In addition to the ray tracing based data set, we consider a comparison case where a simple path loss model is used to estimate the path loss at different positions in the building. We have used a path loss model of the form [10]:

$$PL = PL_{d_0} + 10n \log_{10}(d/d_0) \text{ [dB]} \tag{6}$$

Any multi path effects caused by the building structure are thus not accounted for.

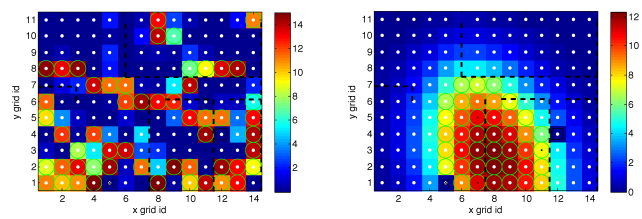
Initially, we fitted this model to the distribution of all measured path losses in the dataset relative to the AP point. Specifically, we used a Least Summed Squared Error optimization to obtain the parameters $PL_{d_0} = -51.6\,\text{dB}$ and $n = 2.022$, shown in Fig. 5(b). Furthermore, the transmit power was adjusted to $4.32\,\text{mW}$ so that the direct transmission yielded the same throughput as with the measurement data.

A. Candidate Policies

For evaluation we consider two location based policies, one which requires an accurate location estimate (grid accuracy) and another which relies on a coarser room-level accuracy. For comparison we consider also the two static policies of always transmitting directly or always using the relay. Since the information collection has an impact on the performance when using the location based policies, we will for the accurate location based policy consider both a delayed information collection and the ideal case with instantaneous collection. The following are the combinations we consider:

Name	Loc. accuracy	Info. collection
Ideal	grid level	instantaneous
Locally optimal	grid level	delayed
Heuristic	room level	delayed
Always direct	-	-
Always relay	-	-

For the heuristic scheme we have defined that it will only use the relay within the two rooms within the rectangle between the two corners (8;1) to (11;6).



(a) Measurement based throughput model (b) Path loss model based throughput model

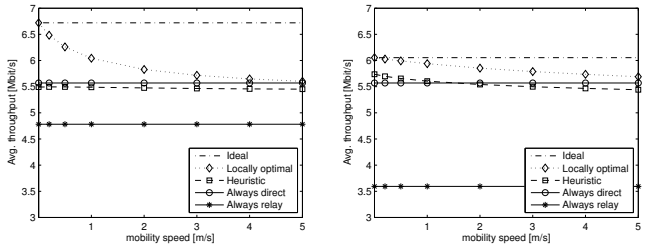
Fig. 6. AP and D positions are marked by a black square $(12, 4)$ and black cross $(5, 1)$, respectively. The color of each grid point shows the achievable relay throughput, if the mobile relay is in that position. The green circles mark the grid points in which the relay throughput exceeds the direct throughput.

Parameter	Value
Measurement delay rate μ	$10^5\ \text{s}^{-1}$
Network loss probability p_{loss}	0
Noise floor	-85 dBm
Ricean K	6
Data frame payload B_{MSDU}	1500 bytes
Average movement speed $\bar{v}$	0.5 m/s
Measurement update rate τ	$1\ \text{s}^{-1}$

TABLE I
Default scenario parameters.

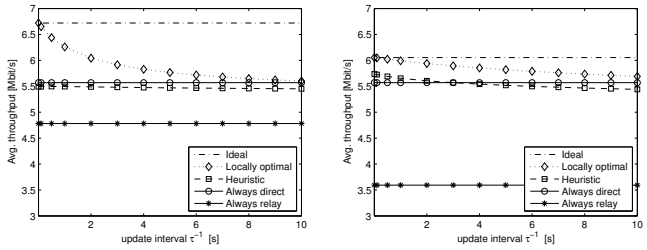
B. Results and Discussion

For evaluating the performance of the different schemes described in the section above, we have applied the mobility model shown in Fig. 5(a), the two throughput models shown in Fig. 6 and the default parameters listed in Tab. I on the Markov Chain model described in Section III. The results obtained when varying the relay movement speed, location information update interval and network delay are presented in the Fig. 7, 8, and 9. Common for all result plots is that the Ideal, Always direct, and Always relay policies are constant, since they are not depending on the varied parameters.



(a) Ray-Tracing data (b) Path loss data

Fig. 7. Average throughput for different policies for varying relay speed.

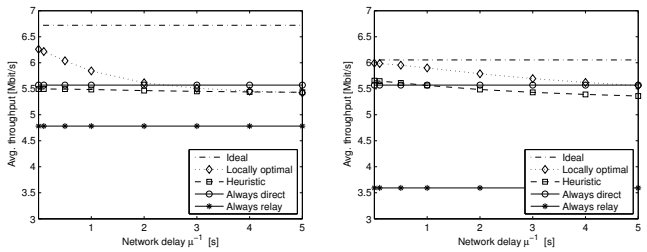


(a) Ray-Tracing data (b) Path loss data

Fig. 8. Average throughput for different policies for varying measurement update rate.

For all parameters being varied with the locally optimal scheme, the ray tracing data results show a bigger impact on performance. This is due to the large variations in achieved throughput between neighbor grid points, caused by multi-path effects in the indoor environment. The path loss data set, on the other hand, does not show the same rapid change between neighbor grid points and the impact of mobility, low update rate and network delays on the locally optimal scheme is therefore less pronounced. Actually, the impact seems identical for the two schemes with the path loss data set, whereas with the ray-tracing data set the heuristic algorithm is hardly impacted, but is also constantly below the Always direct scheme. The heuristic room based scheme does not seem to be a good choice in indoor multi path environments.

Looking specifically at the mobility speed results for the locally optimal scheme in Fig. 7, the ray-tracing data set shows that it is possible to achieve higher throughputs compared to the path loss data set, for mobility speeds in the range of walking speeds (0.5 - 1.5 m/s).



(a) Ray-Tracing data (b) Path loss data

Fig. 9. Average throughput for different policies for varying network delay.

VI. Conclusions and Outlook

Given extracted narrow band path loss information from a database of ray-tracing enhanced measurements of a realistic indoor scenario, this paper presents a Markov Chain (MC) based performance evaluation of location based relaying policies, assuming IEEE 802.11g wireless network equipment. The MC model, proposed in [7] takes into account the inaccuracies caused by a mobile relay's possible movements as well as information collection and network delays.

Our results compare the achieved performance in the ray tracing based data set with the performance achieved using a simple distance based path loss model. We find that while the overall impact of mobility and delays is well accounted for, the variation in performance between neighboring grid points in the indoor building map for the ray tracing data set, due to multi path propagation effects, leads to a significant difference in the results obtained with the two input data sets. A possible improvement could be to artificially include the statistical variation in the path loss model data set.

Due to the measurement/ray tracing data set being used is geographically quite limited in size, it has been necessary to scale down the parameters of the wireless communication, in order to properly showcase a scenario where relaying can be beneficial. As scaling the parameters might introduce some differences compared to considering a larger area, this would be an obvious task for future work.

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