Wave Propagation Using the Photon Path Map

Arne Schmitz
Computer Graphics Group
Ahornstr. 55
Aachen, Germany
aschmitz@cs.rwth-aachen.de

Leif Kobbelt
Computer Graphics Group
Ahornstr. 55
Aachen, Germany
kobbelt@cs.rwth-aachen.de

ABSTRACT

In wireless network planning, much effort is spent on the improvement of the network and transport layer – especially for Mobile Ad Hoc Networks. Although in principle real-world measurements are necessary for this, their setup is often too complex and costly. Hence good and reliable simulation tools are needed.

In this work we present a new physical layer simulation algorithm based on the extension and adaptation of recent techniques for global illumination simulation. By combining and improving these highly efficient algorithms from the field of Computer Graphics, it is possible to build a fast and flexible utility to be used for wireless network simulation. We compute a discrete sampling of the volumetric electromagnetic field by tracing stochastically generated photon paths through the scene. This so called Photon Path Map is then used to estimate the field density at any point in space and also provides local information about the delay spread. The algorithm can be applied to three dimensional indoor as well as outdoor scenarios without any changes and the path-tracing costs scale only logarithmically with the growing complexity of the underlying scene geometry.

Categories and Subject Descriptors

C.2.1 [**Computer-Communication Networks**]: Network Architecture and Design

General Terms

Design, Performance

1. INTRODUCTION

In this work we introduce an algorithm to efficiently and accurately simulate the physical layer of microwave wireless networks which is applicable both to GSM- and 802.11 style wireless local area networks. Especially in the case of Mobile Ad Hoc Networks (MANET) and Wireless Mesh Networks a robust simulation in the development phase is important. This is partly due to the fact that it is hard to acquire enough people and mobile stations for test runs of the algorithms. These simulations can of course also be used for antenna placement with maximum availability of deployed stationary nodes and we show how to use the resulting information in a network simulator.

PE-WASUN'06, October 6, 2006, Terromolinos, Spain.

2. RELATED WORK

There has been done quite some previous work in both the areas of Radio Wave Propagation and Global Illumination. Both share similar roots and goals and this section will show on which work our new technique is based.

2.1 Wave Propagation

There are different possible approaches to wave propagation calculations. All these approaches aim at predicting the advancing of a wavefront through a scene. Upon collision with boundaries of different media the wavefront can be scattered, reflected, diffracted or refracted. Here we will concentrate on algorithms that are mostly based on geometrical optics, i.e., methods that trace elementary electromagnetic waves along rays or straight line segments.

2.1.1 Empirical Models

First one has to distinguish between empirical and deterministic approaches. The empirical methods use a set of parameters to model a function that as closely as possible resembles the pathloss of a signal as described by the advancing wavefront. Popular empirical methods include the Walfisch-Ikegami-Model (WI-Model) [12]. The WI-Model takes into account multiple diffraction on rooftops and is as such almost only suitable for outdoor scenarios in urban microcells, since it fails to model reflections in contrast to our algorithm.

2.1.2 Deterministic Models

Deterministic algorithms use ray tracing techniques to calculate propagation paths. In the wireless network world we distinguish between ray tracing and ray launching techniques. The same techniques are known in computer graphics, where they are also called ray tracing and light tracing, depending on the ray direction. These techniques are accelerated by using space subdivision techniques.

Previous work includes [8, 13, 11], but although these approaches work quite well, they all have drawbacks. Many of them are quite complex and work only either in indoor- or outdoor-scenarios. Our algorithm on the other hand is both simple and flexible.

2.2 Global Illumination

Our algorithm is an extension of the Photon Map [5] which is used to compute the distribution of light on the object surfaces in a three dimensional scene.

Microwave radiation and light are essentially the same phenomenon, but some differences have to be noted. First, microwaves have a much longer wavelength than visible light and so the effect of wave diffraction is relevant, whereas for visible light this can almost always be neglected. Second, in Global Illumination most of the algorithms deal with the appearance of object *surfaces*, but for Radio Wave Propagation we need to deal with field densities in a *volume*.

2.2.1 The Photon Map

The Photon Map was introduced by [5] for global illumination purposes. It is a spatial data structure which stores incoming radiance on 2D surfaces. Each collision of a photon with an object is stored in the Photon Map and the density of the map at a certain point can be seen as the radiance at this point. The Photon Map is generated by the following algorithm, which constructs a path for every emitted photon:

```
For each light source do
   Shoot n photons in random directions
   If photon hits surface decide randomly:
      a) Store, then absorb photon
      b) Store, then reflect or transmit photon
```

The random decision is called Russian Roulette and ensures that an arbitrary number of interactions with the scene can happen, only bounded by the material properties of the objects in the scene. Most techniques used for Radio Wave Propagation allow only for a fixed, but user definable number of reflections or transmissions. Our technique favors paths along highly reflective objects, i.e., only paths that carry a lot of energy are computed. This importance sampling is very useful in the context of wave propagation.

2.2.2 Energy estimation

To get an idea of how bright a surface point should appear, we need an estimator of the photon density. The standard way to do this in the Photon Map method is to use a kernel density estimator (KDE). In the multivariate case of dimensionality d, we use a bandwidth h, a number of samples n and a filter K. The KDE is now defined as:

$$\hat{f} = \frac{1}{nh^d} \sum_{i=1}^{n} K\left(\frac{\|x_i - x\|}{h}\right)$$

In practice it turns out that a cubic filter kernel works best for the Photon Path Map as it will produce a smooth estimation of the field density, as compared to a simple box filter for example.

In the Photon Map algorithm we can build a KDE over the stored photons to get an estimated value for the incoming radiance. The sample set can be efficiently gathered by taking the k-nearest neighbors for the surface point using hierarchical space partitioning, e.g. a kd-tree.

3. THE PHOTON PATH MAP

Our new algorithm extends the idea of the Photon Map to allow not only for the computation of surface radiance but also to get an estimated field strength for every point in space. Therefore we do not only store points of interaction in the map, but also the paths that connect these points as a photon travels through the scene. As a result we get a discrete sampling of paths along the wavefront. Figure 1(a) shows a Path Map for an indoor data set. Here the map is only sparsely sampled and also rays that leave the scene are left out for simplicity.

3.1 Path Generation

The photon paths are built in much the same way as in the classic Photon Map approach. We use a standard photon mapping raytracer that is also used to generate illuminated images of three dimensional scenes. The input is given as a set of triangle meshes, surface materials per triangle and transmitters. The scene geometry is stored in a balanced kd-tree to accelerate the ray intersection tests. The output of the algorithm is a volume image with the simulated field strengths per voxel.

3.2 Ray Bending

The raytracer works as a Monte Carlo path-tracer and reflects, transmits and diffracts the rays as necessary. The diffraction of the rays is a step that is usually not needed for image synthesis, but necessary for microwave simulations. Since we use a Monte Carlo approach for the sampling of the paths we can use the Heisenberg Uncertainty Ray Bending (HURB) by [4], which allows to sample the diffracted field of a ray incident on a diffracting edge embedded in a Monte Carlo path tracing process. This leads to the following algorithm:

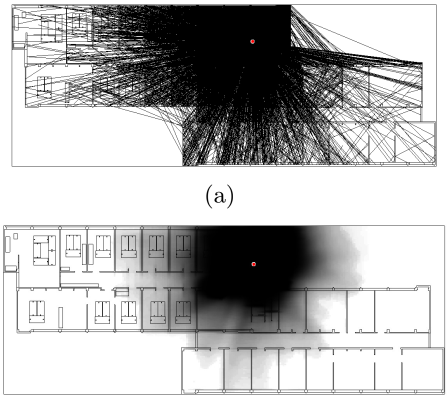
```
PreProcess:
    Find all convex edges and store
    them in a kd-tree

traceHURB:
    1. For a random number of steps
       2. Find nearest intersection w/object
       3. Find nearest diffraction edge
       4. Depending on order of event
          4a. Compute reflected ray, goto 1
          4b. Compute diffracted ray, goto 1
       5. Store path element
```

3.3 Field Strength Estimation

After the ray shooting we have a set of ray path segments. Now we have to determine the path density for each voxel in the output image. The kernel density estimator approach of the Photon Map requires us to find the k nearest photons to a certain point. This is relatively costly when performed on the uniform grid of the volume image. Also only approximate neighbor searches can be made.

Instead of this we do an explicit calculation of the KDE by rasterizing the weighting function of the paths directly. The weighting function for a photon path segment produced by the kernel is similar to a distance function of a cylindric shape. The idea is now to do a scan conversion of this cylindric function that results in a voxelization. Details of this procedure can be found in [9].

The resulting volume image represents for each voxel an approximated stationary field strength. Small scale fadings can be modelled on top of this stationary field. One solution is to use a Ricean Fading model as proposed in [6].



(a)

(b)

Figure 1: (a) A sparsely sampled Photon Path Map in an indoor scenario. (b) The same map, more densely sampled and with the field strength coded by using grey scales. Both images represent the top view of a 3D simulation.

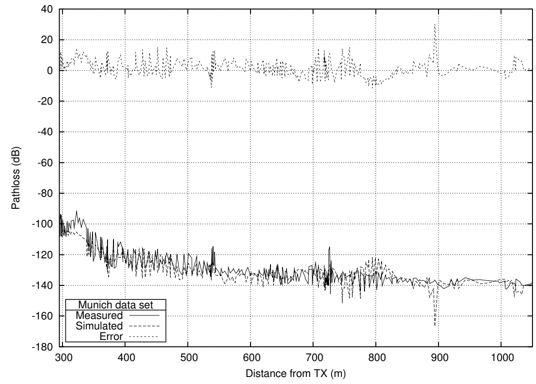


Figure 2: Simulation results for the Munich city center dataset. The lower two curves show the measured and simulated pathloss in dB and the curve at the top shows the error made in the simulation.

3.4 Delay spread estimation

One further advantage of our approach is that it allows the estimation of channel delay spread due to multi-path propagation. Quite a few previous works have developed models and procedures to measure and simulate the delay spread of channels [1, 10, 7]. The knowledge of these particular channel characteristics becomes ever more important for OFDM based schemes, as for example in 802.11 networks.

Our algorithm computes a sampling of the most important paths, where we can generate a delay spread histogram for any point in space. Alternatively we compute the standard deviation of delay spread over the complete volume, which can then later be used to compute a distribution of signal delays in a simulator.

The results from Figure 3 confirms results observed by [7], where we have one delay profile made from a position with line of sight to the sender, and one profile without line of sight, in a corridor. It is well known that corridors in indoor scenarios have strong multipath propagation profiles and thus a large and highly varying delay spread spectrum.

3.5 Small scale fading and interference

Small scale fading happens as a result to Doppler shift generated by moving objects in the scene. This phenomenon is not explicitly modelled by the Photon Path Map, but can be modelled by additional fading models, which depend on the underlying movement models of the simulation. This has been described in more detail by [6]. In particular small scale fadings can be induced by any moving object in the scene, which proves to be very difficult to model. Interference which is due to multiple senders will be handled by the network simulator by testing transmitter ranges.

3.6 Interface with the network simulator

For the simulation of the MANET we use the ns-2 simulation package [3]. In a pre-processing step we compute for a subset of each possible transmitter position one Photon Path Map. For a typical indoor scenario of a medium sized building about 200 positions are usually sufficient.

These maps are then used to do interpolated lookups of the field strength. The ns-2 generates requests for the field strength concerning a certain sender and receiver position. First we determine the k-nearest Photon Path Maps considering the transmitter position and visibility, as induced by obstacles in the scene. The selected maps are weighted by distance and the weighting coefficient is then used to do an interpolated lookup at the receiver position.

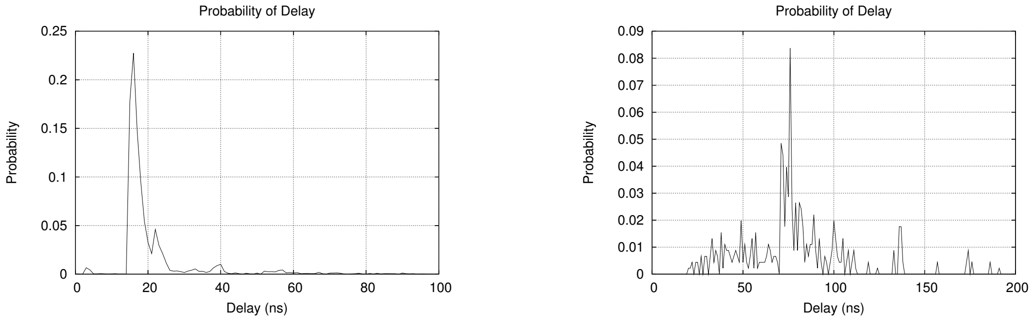
This can be done extremely fast and results in an approximated signal strength at the receiver position. This procedure results in a much more realistic result than the current two-ray-ground physical layer approach in ns-2 while it is only 1.5 to 1.7 times slower. More results are shown in [9]. Also shortly before submitting this work we have implemented this in a real-time framework which allows interactive manipulation of transmitter positions with immediate visual feedback.

4. EXPERIMENTAL RESULTS

We have run the algorithm mainly on three different scenarios for which real measurement data has been available. The first scene is the Munich dataset from the COST 231 project [2], which was originally sampled by Mannesmann Mobilfunk GmbH, Germany. This scene describes a microcell outdoor scenario of a few square-kilometers in size. Figure 2 shows the measured and simulated field strengths as well as the error made.

The other two scenes are indoor scenarios, for which result plots can be found in [9]. The following table shows the simulation results for the different scenes, including the mean error and the standard deviation from the measurements. All results were computed on a 2.2 GHz PC with 2 GByte of RAM.

Scene	Accuracy	Time	Mean error	Std. dev.
Munich	~10 m	6m 53s	3.62 dB	4.68 dB
Indoor 1	~0.2m	12.7s	5.1 dB	6.6 dB
Indoor 2	~0.2m	15.8s	4.5 dB	5.6 dB



(a) (b)

Figure 3: This figure shows the delay spread in the indoor scenario. (a) Delay spread statistics for a position in line of sight to the sender. (b) Delay spread for a position without line of sight on the corridor.

A comparison with other algorithms is somewhat difficult, due to the fact that there are almost no scenes with measurements publicly available which are used by most published works. Also several papers do not mention the used hardware, runtime, target complexity or an error measure. A direct comparison can be made with the Dominant Path Prediction (DPP) algorithm for outdoor scenarios by [11]. Here, the Munich dataset has been used. It can be noted that for large outdoor scenarios our approach is about 10 times slower than the DPP, while our results are slightly better. However with the DPP it is not possible to get information about the delay spread. This is a very important information since it heavily influences channel quality on OFDM channels. So the pathloss alone is not sufficient. Another advantage of our algorithm however is that it is much simpler. It handles 3D scenes very well and processes almost arbitrary geometry in an efficient manner. Since we showed that our approach can be done completely as a preprocessing step, the runtime will not affect a simulation in the ns-2.

5. CONCLUSION

In this work we have presented a wave propagation algorithm with many advantages over existing algorithms. It is physically based and thus can be compared with real life measurements, an improvement of the scenario detail will result in a higher accuracy of the simulation. Standard triangular meshes can be used as input. These meshes can be easily produced for example from CAD-data for indoor scenarios or map data for outdoor scenarios. The algorithm handles indoor and outdoor cases equally well and does not need to be adapted to either case. It is even possible to use mixed scenarios, where urban microcell propagation is combined with, e.g., the reception of a mobile phone in a building.

Another important advantage of this algorithm is that it produces a ray path-structure from which we derive information like the delay spread spectrum and the standard deviation of the delay spread. The paths include all possible combinations of reflection, transmission and diffraction. The path length is arbitrary and determined by the Russian Roulette procedure, which is unbiased.

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