# Truck Localisation in a Mine Using Sparse Observations

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## Abstract

In mining, Fleet Management Systems (FMS) are useful tools for reporting and improving mine efficiency, though comprehensive FMS are expensive to install and maintain. This paper examines an alternative method using a particle filter algorithm to localise a fleet of haul trucks in a mine, providing most of the functionality of a complete FMS without the expensive hardware and installation. Most FMS require constant radio communication with all haul vehicles. The new method described here uses only node to node communication which requires less hardware and infrastructure to operate. The system has shown to be effective using data collected from two mines.

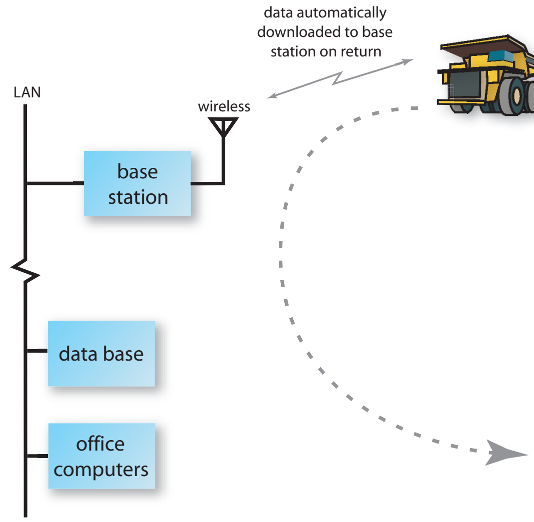


Figure 1: Overview of the Base Station Operations

## 1 Introduction

For a capital intensive industry such as mining, it is important that all resources in the mine are used to their full potential. In particular, the efficient management of haul trucks and diggers can reduce queueing time and in some cases reduce the number of trucks required to haul ore. Fleet Management Systems (FMS) are useful tools for assisting mine planners in achieving these goals by providing the state of the vehicles to monitor performance and find 'bottlenecks' in the mine. A FMS should also be able to keep statistics about the mine operations such as tons hauled, driving cycle times (time to make a round trip to the diggers) and other important information.

To effectivly plan mining operations, a Fleet Management System should be able to provide the location of any vehicle within the mine at any time. This has been generally achieved by providing full wireless network coverage to the operating areas of the mine, allowing the trucks to transmit their location to a central base station. FMS currently available provide this service by installing repeater stations where necessary to obtain full radio coverage to the mine. The down side to this approach is the cost of infrastructure and the re-surveying of the network required when there are any changes to the mining operation. For small to medium mines, or mines where the terrain is not conducive to wireless reception (hilly, thickly vegetated) the cost of this can be prohibitive.

This paper describes a new system where the locations of the haul vehicles are predicted using a localisation filter. The vehicle observations are transmitted from truck to truck during operation, and downloaded to a base station upon returning to the central ore collection point. This data provides the central base station with an update of the last known locations for trucks still driving. The location filters are then updated using these observations.

The first version of a haul truck monitoring system [Nebot *et al.*, 2006] provided the facility to transmit data between vehicles (node to node) without the use of a full coverage network. This paper also describes modifications to this system to provide a more robust network with multihop functionality. The benefit of using this system is that there is no infrastructure required (apart from the base station) and no modifications to this system are needed when there are changes to the mine.

Some initial work is this area was done by The Washington ITS research group [Cathey and Dailey, 2003] and [Cathey and Dailey, 2001]. They use a method of predicting the arrival time of buses at a central location by considering prior knowledge of the bus travel times, and measuring bus speeds along each route. The filter introduced in this paper extends this approach by using prior truck data to propagate the vehicle model. The complexity and non-linearities inherant in this approach means that a linear filter would not work. Section 4 describes how a non-parametric particle filter can work with such a model.

Finally, the experimental results are shown using data collected from the first version of the haul truck monitoring system [Nebot *et al.*, 2006]. The new hardware described in Figure 2 is in the process of installation.

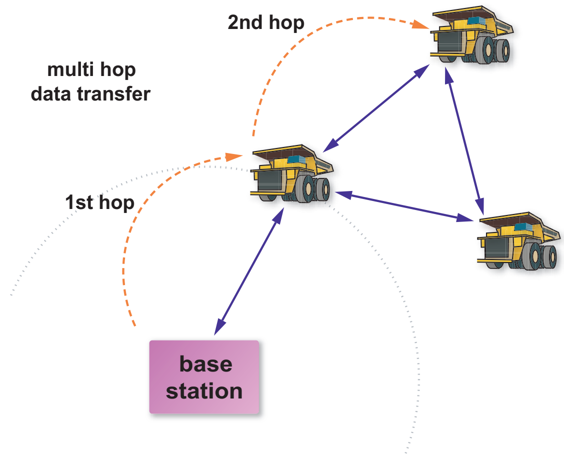


Figure 2: The mesh network allowing multihop data transfer

## 2 Description of the System

A typical mining operation being considered in this paper involves a fleet of trucks hauling ore from a digger to a central location, usually the entrance to a conveyor, or a stockpile. Breaking this operation into discrete tasks, a truck will drive from the central location to the ore face (where the digger is located) and then return to the central location. Throughout this paper, this process will be referred to as a haul trip with the digger location as the destination. The central location will be referred to as the base station, named after the computer at that location.

Depending on the size of the mine there may be one or more diggers, with a number of haul trucks assigned to each digger. The number of trucks assigned to each digger depends on many factors, though this number is usually between two and four in small to medium sized mines.

For the implementation described in this paper, ruggedised computers are installed in each of the haul trucks to collect data from the vehicle in operation. Data is collected from the GPS and other sensors on the vehicle and then automatically downloaded to the base station at the end of each trip. A schematic of this process is included in Figure 1.

The trucks have also been fitted with a mesh topology network to facilitate vehicle to vehicle, and vehicle to base station communication. This type of network allows messages to be sent between nodes on the network either directly, or using another node as a conduit (router). This is useful in a mining situation since it allows communication between network agents that are not directly in range. An example of this is shown in Figure 2. The mesh network was designed to be a robust and self-healing network. It uses a well designed routing protocol [Jacquet *et al.*, 2001] which actively seeks other nodes on the network.

The vehicle to vehicle communication allows the trucks to share their positions when in reception range. This allows each truck to effectively keep a list of the vehicles it has sighted during a trip, which can be relayed to the base station on the completion of a trip. When the base station receives a list of vehicle observations, the localisation filters running on the base station can be updated. Using this method, the trucks become the network conduits transporting information and eliminating the need for complete wireless network covering the mine.

## 3 Representation of the mine

The data collected from the vehicles is used to build a representation of the mine. The most simple method of representing the mine is to consider the location of the truck as a function of distance through a trip. This single dimensional (distance only) model is used to generate a graph of the mine, where the verticies are the intersections and the edges are the roads (see Equation 1 and Figure 4).

Each road (vertex) in the mine is divided into a set of subsections $e_i$ which are stored as vectors (see Equation 1). A subsection vector contains the cartesian coordinates, distance to the start of the $E$ (road), average heading and average speed for the corresponding section of road.

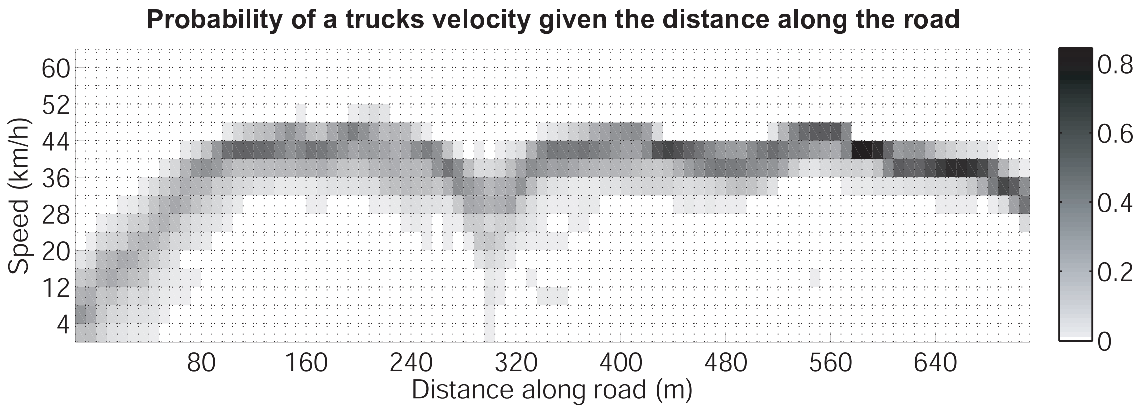


Figure 3: An example of the velocity PDF generated

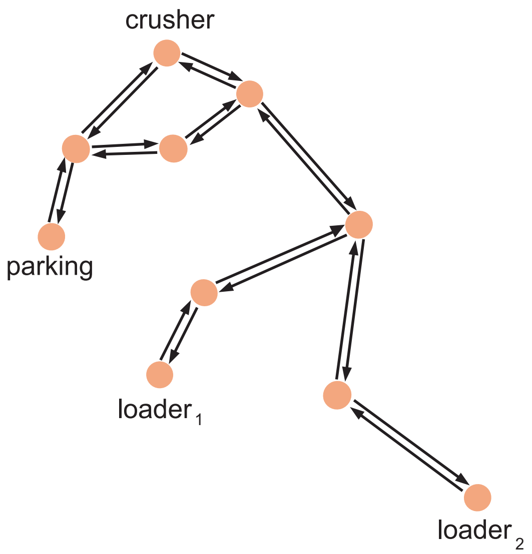


Figure 4: Graph Representation of the Mine

Using graph notation:

$$\begin{aligned} \text{Graph of Mine, } G_{\text{mine}} &= (V, E) \\ \text{verticies } V &= \text{intersections} \\ \text{edges } E &= \text{roads} \end{aligned}$$

where

$$\begin{aligned} E &= e_1 \cup e_2 \cup \cdots \cup e_n \\ e_i &= \text{small section of road} \\ &= \begin{bmatrix} \text{position} \\ \text{average heading} \\ \text{velocity PDF} \end{bmatrix} \end{aligned} \tag{1}$$

The velocity probability density function (PDF) shown in Equation 1 describes the probability of a trucks velocity for a given section of road based on historical data. This PDF is generated using the data gathered over a long period and is constantly updated as new data is collected. An example of a velocity PDF is shown in Figure 3. In this figure the x-axis shows distance along a road, the y-axis shows the probability of a truck travelling at a given speed for each section of the road. The average heading is also calculated from historical data.

The filter and prediction algorithms that are described later require the efficient conversion between cartesian coordinates from the GPS and the equivilant distance along a road in the mine. The implementation allows fast conversion between the coordinate systems (Equation 2), though the details of this process are outside the scope of this paper.

$$\text{GPS Coord.}_{(x,y)} \Leftrightarrow \text{distance to start of E (road)}_{(S)} \tag{2}$$

The number of vectors used to represent a road is chosen to optimise computation requirements while reducing error caused by discretisation. As the number of vectors increase, the error is reduced and the computational requirements grow and vice versa.

## 4 Particle Filter and Prediction Algorithm

The complexity and non-linearities presented in this problem lead to the use of a nonparametric filter, in comparison to a parametric (e.g. Gaussian) filter. Due to the relatively low complexity of the vehicle model for this problem, a particle filter should be able to approximate the location (PDF) of multiple vehicles with reasonable computational power. This approach uses a set of location hypothesis (particles) to approximate the probability density function corresponding to the real truck location. The basis and proof of this approach is outlined in [Thrun, 1981] and [Gordon *et al.*, 1993].

The algorithm takes two main sections; the particle filter and the prediction algorithm, outlined in Figure 5. The filter uses the prediction algorithm for propagating the particles, and observations are received with a delay by other returning vehicles, as shown in Figure 1. The prediction algorithm uses historical data to predict with associated bounds the PDF of the trucks location.

### 4.1 Assumptions for Mining Operations

Listed below are the assumptions made in this system, and these hold for normal mining operations.

- There is only one possible (optimal) path to get to and from the destination, which will be the one selected by the truck drivers.
- The only traffic to consider for a haul trucks is other haul trucks. There may be light vehicles driving around the mine, though these will give way to the much larger haul trucks.
- The destination of the haul truck is known when they leave the base station for a haul trip.

The haul trucks have a limited number of roads that they can traverse due to the nature of a mine and the size of the vehicles. It is also assumed that these vehicles cannot turn around in the middle of a road (only in an intersection).

### 4.2 State-space Model

The mine has been represented in a graph format (see Section 3), so the location of each truck can be considered in terms of the distance travelled into the trip. This makes the trip distance travelled as the only dimension for the state space vector in this filter. Also described in Section 3 is the concept of providing a velocity profile

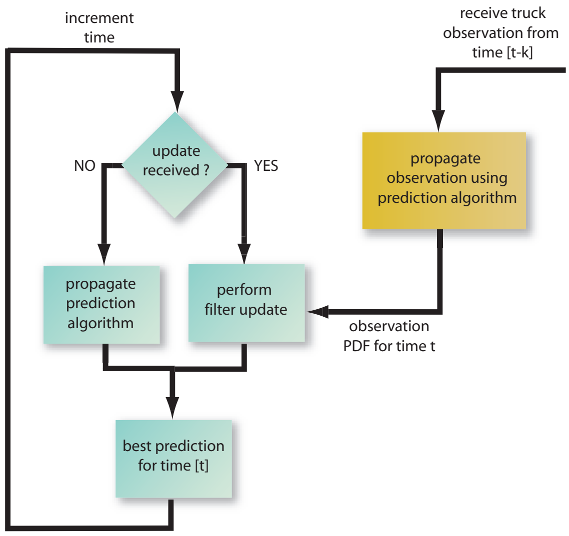


Figure 5: Overview of the Filter/Prediction algorithm

of the roads within the state space, making the velocity profile at each point on the road a function of the distance along the road (equation 5)

A trip is composed of a list of graph elements, starting from the intersection with the crusher then to the intersection containing the destination then returning to the crusher. This is shown in Equation 3.

$$\text{trip}_i = \{V_a, E_{a\to b}, V_b, E_{b\to c}, \dots, V_b, E_{b\to a}, V_a\} \tag{3}$$

The state-space for this filter ($S_i$) is the distance travelled into trip$_i$. From Equation 1, we take the vectors from each road in the current trip and combine to get the state-space $S$ divided into its subsections, becoming Equation 4.

$$\begin{aligned} S_i &= \text{distance into trip}_i \\ &= s_1 \cup s_2 \cup \dots \cup s_n \end{aligned} \tag{4}$$

For the state-space $S_i$, the velocity pdf is also taken from each vector within the graph elements to give Equation 5.

$$\begin{aligned} \text{velocity } v &= f(S) \\ \text{probability density of } v &= P(v|s_i) \text{ for } s_i \in S \\ &= \text{see Figure 3} \end{aligned} \tag{5}$$

### 4.3 Vehicle Model

The vehicle model is derived from:

$$S = \int v \; dt$$

$$S_{t+1} = S_t + \int v \text{ dt for a discrete time step} \quad (6)$$

If the velocity is known for each segment, then assuming that the velocity remains constant within the segment, the propagation model becomes Equation 7. $\int V$ dt essentially describes the change in $S$ during one time step. If, during one time step, the vehicle travels across several sections (multiple $s_i$), the integral becomes the sum of the distance travelled in each section, also shown in Equation 7.

$$\begin{aligned} \int v \text{ dt} &= v_{si} \times \Delta t \text{ within a segment} \\ &= \sum_{i=j}^{k} (v_{si} \times t_{si}) \text{ between segments j and k} \\ \textit{where} & \\ t_{si} &= s_i \times v_{si} \end{aligned} \quad (7)$$

Equation 7 describes the increase in $S$ for a given time step. In practice, the vehicle model will be propagated by a fixed time step, in this implementation set as $\Delta t = 1$. This means that at the end of each time step, the vehicle prediction will likely be somewhere in between the start and the end of a section. The propagation algorithm stores the final location at the end of each time step and the remaining distance in the $s_i$ is used for the next iteration. In this way, the state-space is continuous, because the truck can take any value of $S$ between 0 m and the length of the trip.

The velocity described in Equation 7 is not constant, but forms a probability density as described in Section 3 and Figure 3. For this reason, each particle will implement the vehicle model using velocities randomly sampled from the velocity PDF corresponding to the vehicles location.

$$v_{si} = \text{random sample from } P(v|s_i) \quad (8)$$

This random sampling will cause the particles to 'spread' over time due to the different velocities.

$$\begin{aligned} \text{position of truck } x,\ S_x &= \{s_x^1, s_x^2, \ldots, s_x^n\} \\ &\approx P(S_x) \\ \text{where} & \\ s_x &= \text{an individual particle} \\ n &= \text{number of particles/samples} \end{aligned} \quad (9)$$

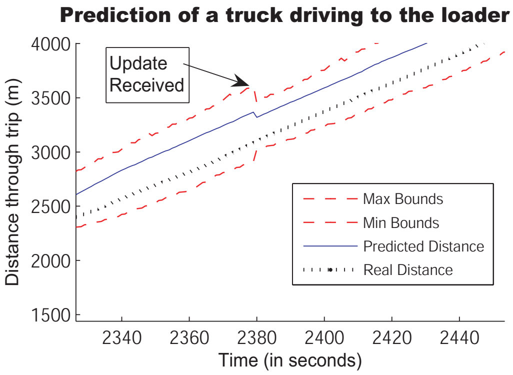


Figure 6: Results zoomed in to show the filter update

For a particle filter, the samples defined in Equation 9 are approximately distributed as $P(S_x)$ [Gordon *et al.*, 1993]. As the number of particles increase, the closer this approximation is to the real distribution. The number of samples chosen is selected to balance accuracy with computational requirements. In testing, 5000 particles were used with a number of concurrent particle filters and the algorithm executed faster than real time.

### 4.4 Implementation and Filter Updates

The algorithm is initialised for a truck when it leaves reception range of the base station. At this time, the last known location of the truck is the initial location for the particles and a number of particles are generated at this point.

When a truck returns, the computer transmits to the base station the last known positions of the other trucks passed during the trip (see Section 2). The filters running for the other trucks can then take these observations and propagate them forward to the current time. This is done using the same algorithm for propagate the particles in the filter. First, a set of particles is created for the observation at time $t_{now-k}$ and then these are propagated forward $k$ seconds. Time $t_{now-k}$ is the time of the last true vehicle observation. The location PDF and the observation PDF can then be used to perform the update by taking the multiplication of these two functions. In practice, the observation PDF is generally much less narrow than the location PDF since the observation PDF is more recent. This means that the resulting filter update will be very close to the observation PDF.

## 5 Results

The algorithm implemented in this paper has been tested using data collected from two mines. This algorithm was successful in predicting the real location of the truck within the given confidence bounds for the journey between the base station and the destination. Figures 6 and 8 show two samples of the algorithm output, with

| | State | Location | Distance through trip |
|---|---|---|---|
| Truck 14 | Estimated | At Loader 1 | 10.94 km, uncertainty [+0.013km, -0.078km] |
| Truck 15 | Estimated | Returning from Loader 2 | 2.27 km, uncertainty [+0.4km, -0.9km] |
| Truck 16 | Estimated | Travelling to Loader 1 | 4.16 km, uncertainty [+0.4km, -0.75km] |
| Truck 38 | Known Position | At Crusher | 15 m |

Table 1: Example of the Output in Table Form

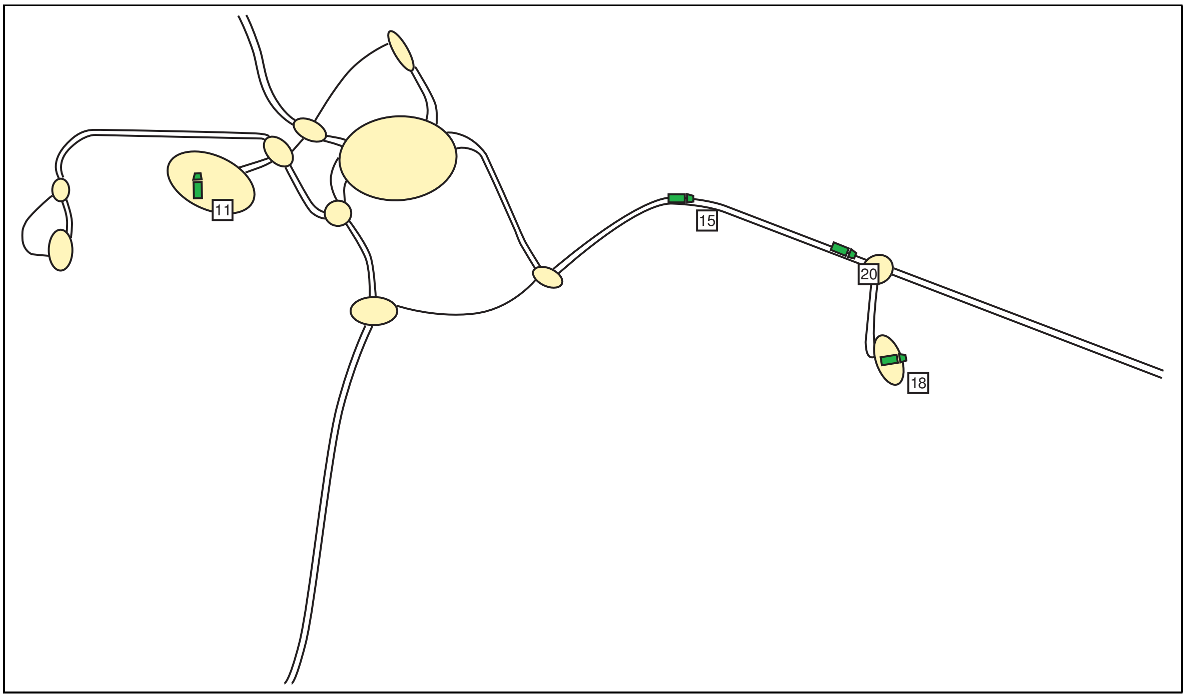


Figure 7: Example Screen shot from the Base Station program. The elipses are intersections, the lines joining them are roads. There are four trucks (labeled with their identifying number) on the screen. The base station is the largest elipse in the centre of screen, currently unoccupied. Truck 11 has stopped at the administration area.

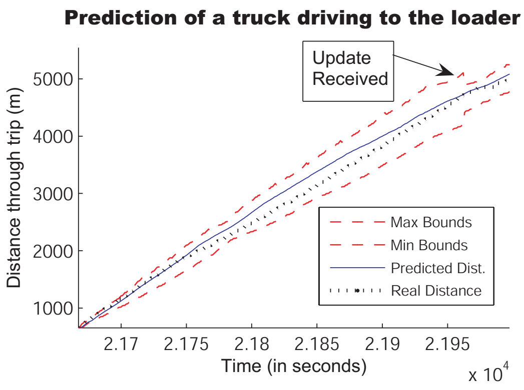


Figure 8: Results from the algorithm

the small dotted line showing the real trucks distance through the trip, and the solid line showing the predicted distance. The dashed lines show the minimum and maximum bounds of the particles. With further research into the modelling of the truck queues at the destination, it is expected that this algorithm will provide accurate predictions for the entire trip.

Table 1 shows the output of the filter in tabular form. In this example, four trucks are being monitored by the base station and three are currently in estimation mode. The uncertainty range of each truck is not symmetrical due to the average velocity being generally closer to the maximum velocity (shown in Figure 3. This leaves the particle density skewed towards the maximum bounds. The uncertainty of truck 14 is small because the truck is at the loader, and the most of the particles predict the truck is queuing at the loader (stationary).

When the system is in operation, the base station provides visual feedback as shown in Figure 7. The output of the algorithms are also available in tabular form stored in a data base (example shown in Table 1). The position data stored in the data base can be used in existing fleet management software.

With the implementation of the new network hardware and with hardware fitted to additional vehicles such as light vehicles and diggers it is expected that the uncertainty will be reduced. For the new network, additional vehicles will act as data conduits to effectively expand the network range through multi-hopping. These vehicles will also help by observing vehicles in the mine and reporting these observations to other trucks and the base station.

## 6 Conclusion

This paper describes a new process designed to provide a real-time and continuous estimate of a trucks location in a mine. Particle filters and a prediction algorithm are used to provide location estimates with confidence bounds.

Results are given using data collected from two mines which show the potential of the proposed algorithms. Since this system uses a minimal amount of hardware there is a potential to bring a cost effective Fleet Management System to mines where more expensive full wireless coverage systems are not feasible.


## Acknowlegements

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