Estimation and Tracking of Excavated Material in Mining

Christopher Innes  
Australian Center for Field Robotics  
University of Sydney  
Sydney, Australia  
Email: c.innes@acfr.usyd.edu.au

Eric Nettleton  
Australian Center for Field Robotics  
University of Sydney  
Sydney, Australia  
Email: e.nettleton@acfr.usyd.edu.au

Arman Melkumyan  
Australian Center for Field Robotics  
University of Sydney  
Sydney, Australia  
Email: a.melkumyan@acfr.usyd.edu.au

Abstract—This paper provides a method for representing, tracking and fusing information on excavated material as it moves through a mining process chain. A constrained augmented state Kalman filter (based on simultaneous localization and mapping principles) is used as the basis for this process. A method for representing the material properties stochastically based on the unique location of the lumped material is also developed. Through the application of this method, correlations between material at different locations can be maintained. This method is validated through real world experiments simulating an open pit mine excavation.

Keywords: Tracking, Data association, Kalman filtering, Estimation.

I. INTRODUCTION

The ability to accurately track bulk material properties through a production chain in industries such as mining, agriculture, civil engineering and many more is highly valuable. In the mining industry, having incorrect estimates of ore grade and quantity in shipping stockpiles can lead to financial penalties for the mine [1]. Improving the quality of information by tracking material through the production process would enable mine engineers to have a more accurate inventory of their product, and provide information enabling greater planning to avoid these penalties.

The motivating application for this research is to track excavated material in an open pit iron ore mine. A typical example of the process in this application would begin with a particular block of material being tasked for excavation. There is likely to be some prior information about the material (ore) quality at the level of the block. The ore tracking system would maintain an estimate of the material until its destination point. For the work in this paper, the destination is considered to be a stockpile. One of the primary aims of this research is to facilitate operation of a fully autonomous mine, where material estimates will be an input into planning and control of equipment.

Currently, most mine sites have large decentralized sensor networks deployed that can be used for tracking excavated material (Figure 1). Common sensors include load cells on excavator buckets, bucket volume fill level estimators, haul truck suspension strut pressures, plant assay sensors, truck volume scanners and GPS vehicle tracking to name a few. However, there is currently no method for fusing information from these sensors into a common system to track the excavated material. Existing methods (discussed in Section II) typically use each piece of data in isolation.

This paper develops a probabilistic end-to-end method for tracking excavated material in a mine site using a heterogeneous network of distributed sensors. The system develops the concept of a discrete set of ‘lumped masses’ of material at different stages through the mining production process. For example, material in an excavator bucket is considered as a ‘lumped mass’ as it is excavated. Multiple ‘lumped masses’ from an excavator are then fused into a new ‘lumped mass’ in a haul truck as it is loaded. This process continues throughout the production chain, and provides an estimate of the location and amount of material at all times post excavation.

The ore tracking system is formulated with a dynamic state vector to enable new ‘lumped masses’ to be created and removed. An augmented state Kalman filter [2] is used to achieve this. This representation supports probabilistic information in a consistent, compact and scalable manner. It also ensures the information is represented in a common form at all stages of the process.

The augmented state filter explicitly maintains the correlations between the ‘lumped masses’ at different stages in the process. These then provide a mechanism to reconcile the excavated material back to the original in-ground estimates. Reconciliation in the mining industry is the process of comparing the actual quality and amount of material mined from a designated area with the expected output of that area from the prior model. It is useful as a tool to validate geological models and mine plans. Reconciliation is typically performed on monthly (or longer) schedules which reduces the usefulness of the data for planning. A real-time reconciliation of quantitative properties is possible using the framework discussed in this paper.

This paper is organized as follows. Section II will outline the current approaches to material tracking on mine sites. It will also cover possible methods for tracking, representation and perception of material. The ore tracking problem is then developed in Section III. Section IV presents results of the system described in this paper on representative mining scenarios with real-world data at two different scales. Section V discusses the results and conclusions are presented in Section VI.
II. RELATED WORK

Research in the field of integrated real-time material tracking in mining is very limited. The state of the art is represented by commercial products from companies such as QMASTOR [3] and Snowden [4]–[6] which provide basic deterministic estimates at different locations in the system. The Dispatch system from Modular Mining [7] also provides a limited degree of ore tracking during the haul cycle. It has database fields for a material type, which is recorded with the vehicle GPS position. However, the material properties are not estimated online. The current practice in mining is assume all trucks carry a common constant percentage of their maximum load. This value, termed a ‘load factor’, is essentially the average mass of material moved by trucks calculated over a long time line. The method, although accurate over large time frames, does not represent the actual material movements in a haul truck on a haul by haul basis. At this shorter time frame, loads are prone to fluctuations based on operator skill through over / under filling of trucks and excavation of material outside of the designated mining area. It also relies upon the quality of initial in ground estimates of the material being excavated.

Substantially more work has been carried out on methods for modeling specific stages in the mining process. Robinson [8], for example, looks at the variance on different blended stockpile configurations. Giacaman et al. [9] describe a forecast modeling system for the loading and transportation of material to a stockpile, this is used to predict the effect of changed equipment carrying capacity. Sensogut and Ozdeniz [10] describe a statistical study of a stockpile, using finite element analysis to predict the behavior of a stockpile.

The techniques for ore tracking used in this work are more closely related to target tracking and autonomous vehicle localization. In particular, the augmented state estimation method developed here can be likened to the Simultaneous Localization and Mapping (SLAM) problem widely used in robotics [11]. However, instead of dynamically changing the state vector to add features to a map, we dynamically change the state vector to add or remove lumped masses of excavated material. The augmented state representation is also used to constrain estimates to preserve mass through the system. Constrained Kalman filters have been developed to ensure that physical real world constraints are incorporated into a Kalman filter framework. An example of this in Simon and Chia’s paper [12], which describes a method for state equality constraints. Rao et al. [13] show a method for horizon constrained filtering which can be used to solve nonlinear constraints.

Utilizing visual sensors to estimate properties, such as volume, in a mining environment is particularly challenging due to the large amounts of dust present on site (Figure 2). Sensors such as a millimeter wave radar [14] would be useful in this domain due to its ability to penetrate through dust. Being able to define a surface using a 3d point cloud is a vital component when estimating volume. Some other systems currently used in observation of material at various stages in the mining processes include autonomous estimation of haul truck contents (Mass, Volume) online. This has been tested live in research by the CSIRO [15] and commercialized by
Transcale [16]. The use of hyper-spectral camera’s [17] has also been used to determine intrinsic material properties at different stages of the mining process. Appropriate sensor observation models for estimating material properties also has many similarities with the observation models used in climate and weather prediction systems [18]. This type of research will be essential in realizing a complete autonomous systematic estimation system of excavated material which can be implemented at a open pit mine site.

III. PROBLEM FORMULATION

A. Lumped Mass Model

The lumped mass model is a representation for discretizing the excavated material into manageable components based on their physical location. This is done to reduce the complexity of the estimation problem into smaller manageable parts. The lumped mass model implies that material is estimated based on its physical separation from other lumps of material. A lumped mass representation can be written as:

\[ P(X_n) \]  

Where:

\[ X_n = [M, V, Fe, SiO_2, Al_2O_3, Origin]^T \]

\[ X_n \] is a vector of material properties to be estimated. Where \( n = A \) represents the location identifier for each lump (e.g. Excavator Bucket, Haul Truck, Stockpile), \( M = \text{Mass}, V = \text{Volume}, Fe = \text{Iron\%}, SiO_2 = \text{Silicon Dioxide\%}, Al_2O_3 = \text{Aluminium Oxide\%}, \text{Fragmentation} = \text{Ore Fragmentation Level}, \text{Origin} = \text{Co-ordinates of where original material was located in-situ} \). Although the intrinsic properties are included here for completeness, the work in this paper will focus specifically on forming the problem with mass and volume.

A probabilistic estimate will exist for each of the listed material properties defined in the vector \( X_n \).

Mass is used as the measure in estimating other intrinsic material properties when combining lumps of material. The alternate selection would be to use the volume of material present in lumps. Mass and volume represent the two qualities of lumped material which can measure the quantity of the material present at any location. Typically however, mass is a more readily measurable quantity compared to volume. The majority of volume estimation techniques on this scale measure bulk volume. Bulk volume is the volume of area the material occupies including the gap spaces between lumped material. Volume can be extrapolated from this by determination of the bulk factor.

\[ B_f = \frac{V_b}{V_t} \]  

Where \( B_f = \text{Bulk Factor}, V_b = \text{Bulk Volume}, V_t = \text{Volume} \). Depending on the consistency of the material and the configuration in the space which it is occupying, this can lead to variations on the bulk factor.

B. Data Fusion Engine

1) Representation: There exists many possible approaches to probabilistically maintaining the estimates of material at different locations. For the purposes of this work, a Kalman filter framework was used due to its simplicity and compact representation.

The standard linear Kalman filter equations are as follows:

**Prediction Step:**

\[ x_{k+1} = Fx_k + Bu_k + Gq_k \]  

\[ P_{k+1} = FP_kF' + GQ_kG' \]  

Where, \( u_k \) (linear control input) and \( q_k \) (system noise) will be assumed to be 0. \( F \) is known as the state-transition matrix, and describes how the states in vector \( x_k \) will change after a given process. \( P_k \) is the covariance matrix describing how the different states relate to each other. \( Q_k \) and \( G \) denote respectively system noise and a projection matrix of that noise onto estimated states.

**Update Step:**

\[ v_{k+1} = z_{k+1} - Hx_{k+1} \]  

\[ S_{k+1} = HPH' + R \]  

\[ W_{k+1} = P_{k+1}H(S_{k+1})^{-1} \]  

\[ x_{k+1}^+ = x_{k+1}^- + W_{k+1}v \]  

\[ P_{k+1}^+ = P_{k+1}^- - W_{k+1}S_{k+1}W_{k+1}' \]

Where, \( z \) is the State Observation Vector, \( H \) describes how observation vector applies to state vector. \( R \) is the Sensor Noise, \( v \) = Innovation (Error between observed states and corresponding predicted states) \( S \) = Innovation Covariance and \( W \) = Kalman Weighting which describes how much weight
to apply to the sensor observation compared to the original estimate on affected states.

When choosing to model the amount of material at each location a simple solution is to dedicate a Kalman filter for each location. This choice would be beneficial in that all the filters would have state vectors with a fixed size. However, the multiple instances of separate Kalman filters have a major drawback in practice. The lumped material estimates are correlated to each other when they originate from the same grade block. This correlation will be shown to be crucial in ensuring system mass consistency and reconciliation. This correlation is not inherently maintained in a multiple instance Kalman filter approach.

To maintain the correlations in the system, an Augmented State Kalman Filter is used. The key difference from standard Kalman filtering is that the system has a state vector which is dynamic. The state vector expands and decreases as the amount of physically unique lumps of material in the system evolves over time. Mathematically, this can be seen in Equation 11.

\[ X_s = [X_1, X_2, ..., X_{j-1}, X_j]^T \]  

\( X_s \) is a vector space with \( j \) vectors. The vector \( X_i \in X_s \), where \( i = [1, 2, ..., j - 1, j] \), represents a physically unique lumped mass. \( X_i \) can contain states such as those showed in Equation 2. \( X_s \) effectively therefore contains all states to be measured in the system. Given this information \( X_s \) can be seen as the equivalent to the state vector \( x_k \) commonly given in Kalman filtering literature.

Through specific constraints on the applied system models, a system is developed which consistently maintains the correlations between parent and child lumps (and their children) as material moves through the process chain.

2) Initializing and Removing Lumped Mass States: Initializing and removing new lumped mass vectors \( (X_n) \) into the system is a straightforward task and follows very closely the equations for initializing a new landmark into a SLAM system. Equations 12 - 13 below explain the process of initializing a new state.

\[ x_{k,n} = \begin{bmatrix} x_k \\ X_n \end{bmatrix} , P_{k,n} = \begin{bmatrix} P_k & 0 \\ 0 & \sigma^2_{X_n} \end{bmatrix} \]  

\[ x^#_k = Ax_{k,n}, P^#_k = AP_{k,n}A^T + BQ_{k,n}B^T \]  

Where \( A \) and \( B \) are design matrices used to initialize the new states correlations to previous states in the state vector and covariance matrix. \( x^#_k \) = the state vector post initialization of the new lumped mass. \( P^#_k \) = the covariance matrix post initialization.

Take a very simple example of a filter with one existing lumped mass. For this example the existing lumped mass is a stockpile which an excavator will remove material from. The only property to estimate is mass \( (X_n = [m]) \). Assuming that the prediction model noise is incorporated during initialization, the equations below describe the loading process and the development of the correlations between the two lumped mass states. Variables:

\[ x_{k,n} = \begin{bmatrix} m_{stockpile} \\ m_{excavator} \end{bmatrix} \]  

\[ A = \begin{bmatrix} 1 & -1 \\ 0 & 1 \end{bmatrix}, B = \begin{bmatrix} 1 & -1 \end{bmatrix} \]  

\[ Q_{k,n} = \begin{bmatrix} 0 & 0 \\ 0 & \sigma^2_{excavator} \end{bmatrix} \]  

Result:

\[ x^#_k = \begin{bmatrix} m_{stockpile} - m_{excavator} \\ m_{excavator} \end{bmatrix} \]  

\[ P^#_k = \begin{bmatrix} \sigma^2_{stockpile} + \sigma^2_{excavator} & \sigma^2_{excavator} - \sigma^2_{excavator} \\ \sigma^2_{excavator} - \sigma^2_{excavator} & \sigma^2_{excavator} \end{bmatrix} \]  

As seen from the results above the system behaves intuitively. The mass in the stockpile is reduced by the mass in the excavator. The significant result from this process is the off-diagonal terms being equal in magnitude but opposite in sign to the excavator mass state. This fact will be pivotal when fusing new information about the excavator mass state at a later time.

Removing lumped mass states and their correlations when the lumped mass is removed from the system or combined with another lumped mass is important to ensure the conservation of mass in the system is upheld. Practically it also reduces the complexity in the system (reduced covariance matrix size) enabling faster operation. Removing a lumped mass is performed when a system process removes all lumped material from a unique location and it is combined with another lump (or initialized into a new lump at a new location). Mathematically, this process involves removing the rows and columns associated with the lumped mass in the covariance matrix \( (P_k) \) and state matrix \( (x_k) \).

3) Modeling Quantitative Lump Properties: Quantitative lump properties are those which define the amount of material present at each lumped mass location. These are the properties of mass and volume. Previously an example initialization was shown which involved modeling a quantitative lump property from a stockpile to an excavator. The modeling in that example can be generalized for any process with quantitative lump properties as, using the Kalman filter Equations 4 and 5.

Variables:

\[ x_k = \begin{bmatrix} \omega_1 \\ \omega_2 \end{bmatrix} , F = \begin{bmatrix} i & j \\ k & l \end{bmatrix} \]  

\[ Q_k = \begin{bmatrix} \sigma^2_1 & 0 \\ 0 & \sigma^2_2 \end{bmatrix} \]  

Assume that \( Q_k = 0 \).
the equation becomes:

\[ x_{k+1} = \begin{bmatrix} i\omega_1 + j\omega_2 \\ k\omega_1 + l\omega_2 \end{bmatrix} \]  \hspace{1cm} (21)

\[ P_{k+1} = \begin{bmatrix} i^2\sigma_{\omega_1}^2 + j^2\sigma_{\omega_2}^2 & lj\sigma_{\omega_1}^2 + ik\sigma_{\omega_2}^2 \\ lj\sigma_{\omega_1}^2 + ik\sigma_{\omega_2}^2 & l^2\sigma_{\omega_1}^2 + k^2\sigma_{\omega_2}^2 \end{bmatrix} \]  \hspace{1cm} (22)

In order to constrain the problem to ensure linearity in correlations \( i \) and \( l \) must equal one. With this information the equation becomes:

\[ x_{k+1} = \begin{bmatrix} \omega_1 + j\omega_2 \\ k\omega_1 + \omega_2 \end{bmatrix} \]  \hspace{1cm} (23)

\[ P_{k+1} = \begin{bmatrix} \sigma_{\omega_1}^2 + j^2\sigma_{\omega_2}^2 & j\sigma_{\omega_1}^2 + k\sigma_{\omega_2}^2 \\ j\sigma_{\omega_1}^2 + k\sigma_{\omega_2}^2 & \sigma_{\omega_1}^2 + k^2\sigma_{\omega_2}^2 \end{bmatrix} \]  \hspace{1cm} (24)

This results shows that in material transfer process cases \((j, k = +1, 0, -1)\) the variance will linearly add to each state dependent on the process occurring. This is an important result when considering how to implement a mass loss model consistently.

4) Mass Loss Modeling: Modeling and observing the mass loss in each process (e.g. Figure 3) of lumped mass system is of vital importance. It is required to ensure that the estimates do not become positively or negatively biased. Figure 3 is an example of how in a mining system, the amount of material estimated and observed in a bucket does not neatly transition fully into the waiting haul truck. These system losses can be modeled in the same way as initializing a new lump of material into the system shown in Equations 12 - 13.

In Figure 3 the mass loss lump would be initialized as a subtraction from the estimate of material in the excavator bucket. This lump would then be transferred back to the original block to where the material was mined and removed from. In mining, generally a dozer will push any loose material back into the area of excavation. This following is the equivalent matrix operation:

\[ x_k = \begin{bmatrix} m_{\text{stockpile}} \\ m_{\text{excavator}} \\ m_{\text{excav.loss}} \end{bmatrix}, \quad F = \begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & -1 \\ 0 & 0 & 1 \end{bmatrix} \]

5) Reconciliation and Conservation of Mass: In bulk material tracking it is important to ensure that material is not ‘invented’. Take again the simple example case of modeling an excavator loading material from a stockpile using two separate Kalman filters. One filter for the stockpile and the other for the excavator bucket. When fusing new information about the material in the excavator bucket, there is no automatic method to update the material in the stockpile to reflect the correlation between the two lumped materials. The excavator bucket can be carrying more or less material then what is estimated to be removed from the original stockpile. Thus after fusing in new information there is a discrepancy of total mass in the system from what is originally estimated.

This problem can be overcome using the augmented state filter and general equations for mass transfer shown in Equations 19 – 22. The correlations developed in the system modeling act as natural constraint of mass in the system, preventing the ‘invention’ or unexplained disappearance of material. This can be proved by looking at the co-variance developed between a state and other states.

Take as an Example: Observing \( \omega_2 \) (From Equation 23).

\[ P_kH_T \] is used in calculating the Kalman Gain, it is a column vector containing the variance on the observed state and its co-variance to other states.

\[ P_kH_T = \begin{bmatrix} j\sigma_{\omega_2}^2 + k\sigma_{\omega_1}^2 \\ \sigma_{\omega_2}^2 + k^2\sigma_{\omega_1}^2 \end{bmatrix} \]  \hspace{1cm} (25)

Given \( j \) and \( k \) is controlled to take one of the discrete values \([-1, 0, 1]\), the relationships developed through the system models will remain linear since \( k^2 \) will always equate to 0 or 1. It is under these circumstances that the conservation of mass principle can be maintained. By extrapolating this to multiple states which develop over time, it is possible to harness this property for other uses such as probabilistic reconciliation.

One example implementation can be achieved by instead of in the example shown in Equation 14 - 16 where material is subtracted from the original stockpile; the stockpile estimate is left unaltered. By adding a new special reconciliation state initialized with 0 mean and variance. Material removed can be added to this state and conversely material added can be subtracted. This example process can be shown in Equation 26.

\[ x_{k+1} = \begin{bmatrix} m_{\text{reconcile}} \\ m_{\text{excavator}} \end{bmatrix}, \quad F = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \]  \hspace{1cm} (26)

This will result in a state which in this example will track the net movement into and out of that designated stockpile. This could be applied to a mining grade block, and can determine the amount of material removed. By taking a mock observation of this state with estimated mean and 0 variance, the location and mean amount of material removed from the original stockpile can be viewed in the vector \( P_kH_T \) post observation.
IV. EXPERIMENTS

A. Small Scale

The small scale data set, or ‘toy scale’ data set was generated by using equipment on a very small scale to simulate the out of ground mining processes. The small scale experiments data sets are performed with approximately $3L(0.003m^3)$ of material in total. The advantage of using this small scale is that measuring the properties of the material (volume, mass) at the different stages is significantly easier than when the experiment is scaled up in size. The planning, personnel and time required to run each experiment is also significantly reduced in comparison. Small scale experiments also allow precise measurements and control over processes, giving a ground truth upon which to compare results with to ensure the system is consistent.

The process and scale of the experiment can be seen in Figure 4. The mass was measured by digital kitchen scales (+−1g accuracy) and a measuring cylinder with 5ml gradients. Each excavator bucket and haul truck load were measured by these two sensors. In order to simulate losses for the excavator bucket, the assumption was made to return material which was did not arrive in the haul truck from the excavator bucket back to the grade block. Before doing this, the losses are measured using the aforementioned sensors. Losses generated over the haul truck to final stockpile stage are measured for each truck and then stored in a separate container to simulate generally unrecovered material over those states.

B. Large Scale

A larger scale experiment was designed to represent the same processes which occur on a real mine site. The aim of this is to create a more realistic data set in regards to both the processes of moving the material in the given scenario as well as the available information and its format. The process scope is still limited to moving material from an original Stockpile to a ROM Stockpile (See Figure 4). The material used in this experiment is a uniform density beach sand blend to allow the assumption of constant density.

The equipment used to move the material included a front end loader of approximately civil construction scale as well as a 3T dump truck. These can be seen in Figure 5.

At each location (Grade Block, Excavator, Haul Truck, ROM Stockpile) a survey scan was performed. Volume was calculated using the survey data to make observations on the excavator bucket as well as to initialize the original stockpile. Mass data was gathered for the haul truck loads only. The surface scan data was acquired by using a ‘Riegl Surveying Laser’. The mass of the haul truck load was collected by using a set of CAS RW-10P (10T Capacity) [19] truck scales.

V. DISCUSSION

A. Small Scale

The residual plots seen in Figures 7 and 8, show the consis-tency of the mass at the excavator and haul truck locations. Volume observations are used as inputs to the system at these locations. Mass observations are used as the measure of ground truth given the accuracy of this sensor. The horizontal axis on each graph represents the load number, the vertical axis represents the residual value. Two standard deviation confidence intervals are included. Table I gives a comparison between the material estimated as haul truck losses and the material located in the destination ROM stockpile state with the ground truth of those respective states. The result of adding the mass estimated in the system at the end of the experiment compared to the initial stockpile estimated mass shows how the conservation of mass in the system holds (The values are equivalent). Figure 6 gives an example of how the reconciling principle works in practice. It begins with a 2 state system showing one lump location of the initial stockpile. A prediction of material in the excavator bucket from this stockpile is then made. A sensor update showing more material in the bucket is then performed. This update process on the excavator bucket can be shown to reconcile the discrepancy from increased mass in the bucket with the previous prediction of material removed from the initial stockpile.

Using this framework, a consistent probabilistic real-time inventory of material at any location is possible. Material can also be reconciled in real-time. In contrast, current systems provide deterministic estimates of material at limited locations.
Figure 6. Reconciliation using correlations system example from initial stockpile to excavator bucket.

Figure 7. Excavator bucket residual plot with 2SD boundaries for small scale mass / volume experiment.

Figure 8. Haul truck residual plot with 2SD boundaries for small scale mass / volume experiment.

(e.g. averaged haul loads). Reconciliation is done with a delay of possibly months.

B. Large Scale

Preliminary results from the large scale system experiment are positive. One of the main obstacles in verifying the system is obtaining an accurate measure of ‘Ground Truth’ at certain locations for different properties. It can be obtained for mass at the haul truck location given the accuracy of the truck scales is very precise. Volume estimates for this location can be obtained under the assumption of a constant known density.

The generally accepted value for density of sand varies based on the conditions the sand is placed under (dry, wet, combined with other materials etc). These values range from \( \approx 1600 \) kg (dry) - 1900 kg (wet) [20]. The density of the material used in the large scale experiment is calculated to be 1674kg. Appropriate density calculated is critical when making the assumption of constant density given that mass and volume will be directly correlated through this value.

Figure 9 shows a residual plot at the haul truck location for mass. Each truckload (the horizontal axis) consists of 3 buckets loads of material from the initial stockpile. The final truckload has only 2 bucket loads of material which is the reason for the reduction in variance on the final haul truck load. Each bucket load is initialized with a general expected load (and variance) based on the carrying capacity of the excavator bucket. A bucket volume sensor is used to estimation the volume of material in each bucket load. This information is fused with the initialized estimate. By assuming the constant density model, it is possible to test to see if the system remains consistent comparatively to the ground truth estimate at the haul truck location. As seen in Figure 9, the residual (vertical axis) remains within the 2 \( \sigma \) confidence limits. Table II shows that over the experiment, the reconciled excavated material encapsulates the higher accuracy initial stockpile estimate.

<table>
<thead>
<tr>
<th></th>
<th>Initial Stockpile Estimate</th>
<th>Mean[g]</th>
<th>2( \sigma )</th>
<th>Ground Truth[g]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mass</td>
<td>13815</td>
<td>30</td>
<td>13815</td>
<td></td>
</tr>
<tr>
<td>Material Left In Stockpile</td>
<td>Mean[g]</td>
<td>2( \sigma )</td>
<td>Ground Truth[g]</td>
<td></td>
</tr>
<tr>
<td>Mass</td>
<td>18.2</td>
<td>88</td>
<td>30</td>
<td></td>
</tr>
<tr>
<td>Haul Truck Losses</td>
<td>Mean[g]</td>
<td>2( \sigma )</td>
<td>Ground Truth[g]</td>
<td></td>
</tr>
<tr>
<td>Mass</td>
<td>1379.7</td>
<td>204</td>
<td>1351</td>
<td></td>
</tr>
<tr>
<td>ROM Stockpile</td>
<td>Mean[g]</td>
<td>2( \sigma )</td>
<td>Ground Truth[g]</td>
<td></td>
</tr>
<tr>
<td>Mass</td>
<td>12447</td>
<td>222</td>
<td>12442</td>
<td></td>
</tr>
</tbody>
</table>

Table I

Comparison of System Estimates and Ground Truth in Small Scale Experiment.
C. Scalability

Figure 10 shows the sparsity of the covariance matrix in an example experiment. In this example, the lumps are not removed or zeroed in order to show how the system correlations are developed over time. The important aspect is the level of sparsity present. The most numerous equipment and corresponding unique lump locations is present in the haul trucks. At any point in time this equipment will only be correlated to the point of excavation and then that correlation transferred to the stockpile once it is unloaded. Given that material transfer equipment is the most frequent on a mine site, and most bulk material transfer operations in general, the covariance matrix will remain highly sparse.

VI. CONCLUSION

This paper develops a probabilistic representation of lumped bulk material and a framework for tracking this material through a production chain. A method for fusing data from information sources in a distributed mining network is presented. The framework is developed using an augmented state filter with constrained system models. This provides a method for allowing probabilistic reconciliation of material while ensuring that the total mass in correlated states remains constant. Experiments are shown to prove the concept over a small scale in a highly controlled and fully measurable environment. Preliminary results from large scale testing are also included to show how the method can be applied in a real world application. The results are promising and show that it is likely that this system will scale up with larger equipment and material. Future experiments aim to provide greater validation for consistency and scalability of the current approach.

This research is ideally suited for application in the mining industry, although the fundamentals (such as a augmented state filter framework) can be applied across a range of other bulk material handling and processing industries.

ACKNOWLEDGMENTS

This work is supported by the ACFR (Australian Centre for Field Robotics) and the Rio Tinto Centre for Mine Automation.

REFERENCES


Table II
INITIAL ESTIMATE COMPARED TO PROBABILISTIC RECONCILED ESTIMATE IN LARGE SCALE EXPERIMENT.

<table>
<thead>
<tr>
<th>Init. Stockpile Estimate</th>
<th>Mean[Kg]</th>
<th>2σ</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mass</td>
<td>21655</td>
<td>63</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Reconciled Estimate In Stockpile</th>
<th>Mean[Kg]</th>
<th>2σ</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mass</td>
<td>22171</td>
<td>1350</td>
</tr>
</tbody>
</table>