# Image based interface level control in a separation cell

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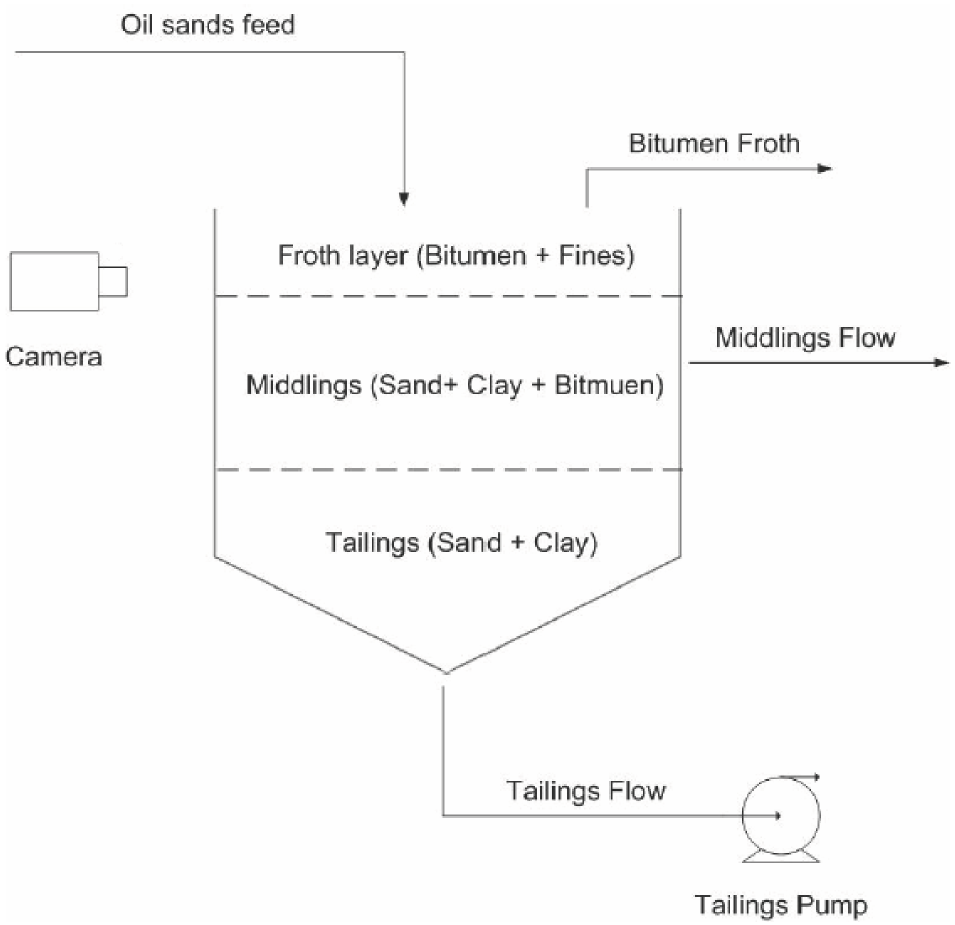
# Problem Description




Schematic of a separation cell

# Problem Description – Motivation

- The interface level between the Bitumen froth and the middlings affects the froth quality and hence influences process economics.
- A good regulation of the interface level improves froth quality, reduces Bitumen losses and results in economic gains (million of dollars per year).
- Problem in automatic control of the interface level is the lack of safe and reliable sensors for interface detection.
- Conventional sensors such as Capacity probes give very crude estimates; Nuclear density profilers have been abandoned due to concerns over safety.

# Separation cell 6 at Suncor Energy Inc.

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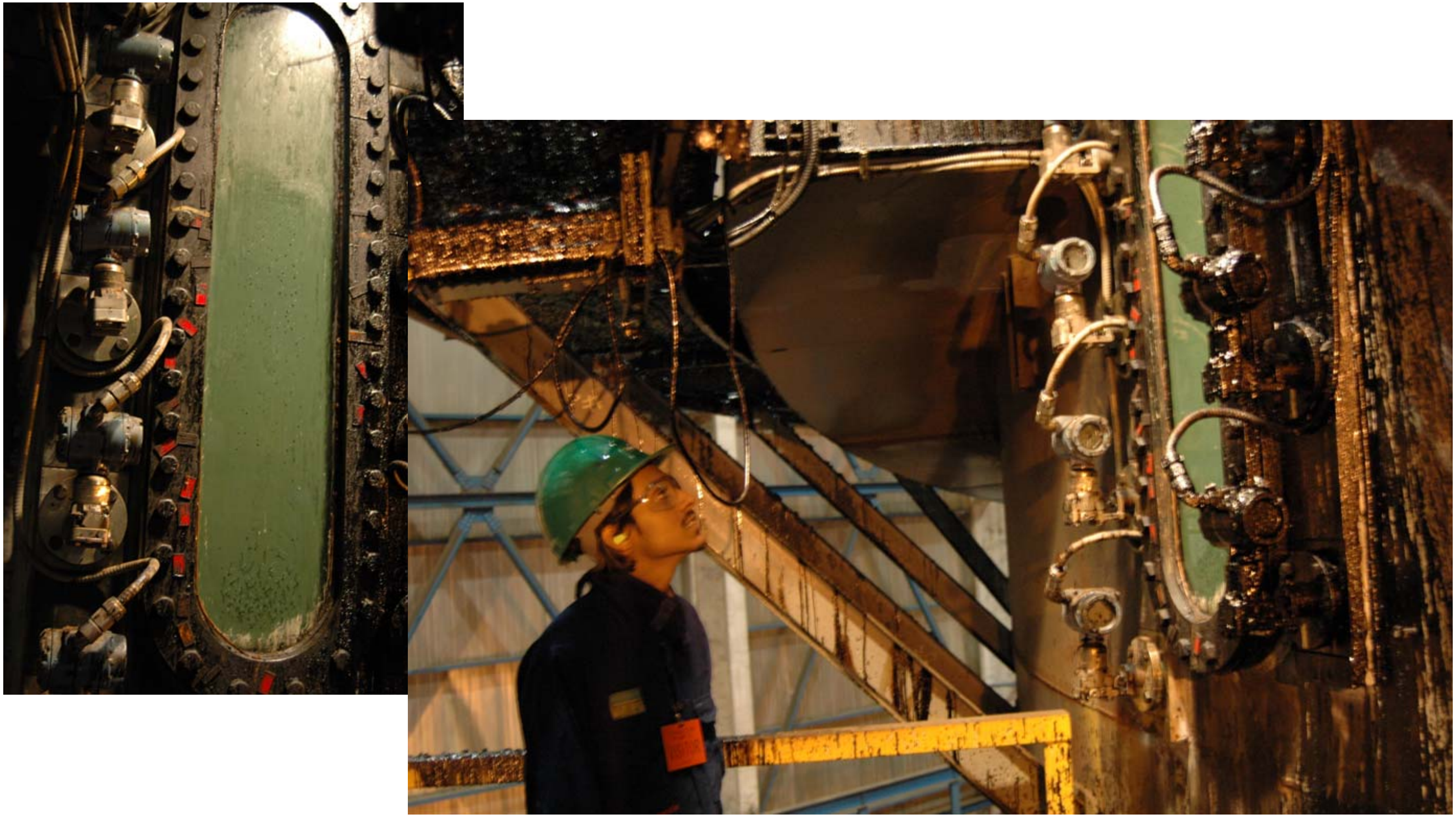
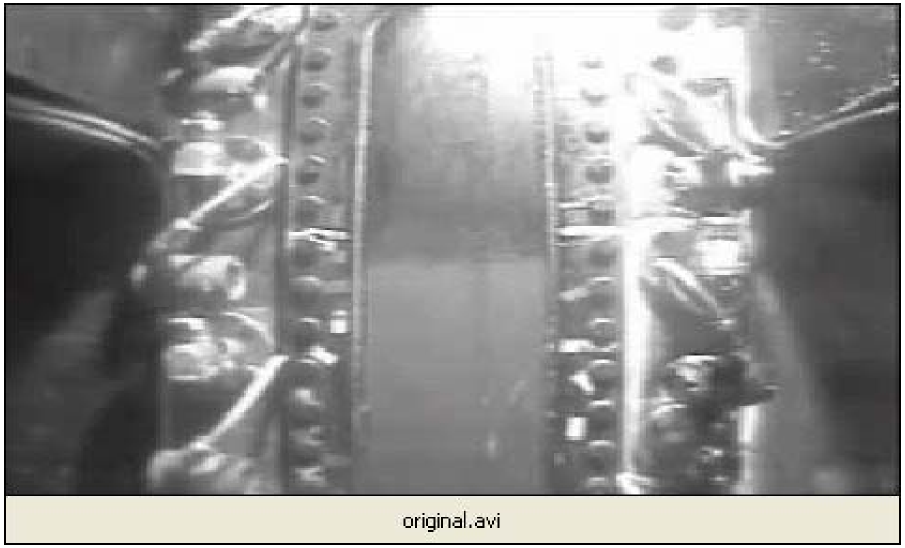


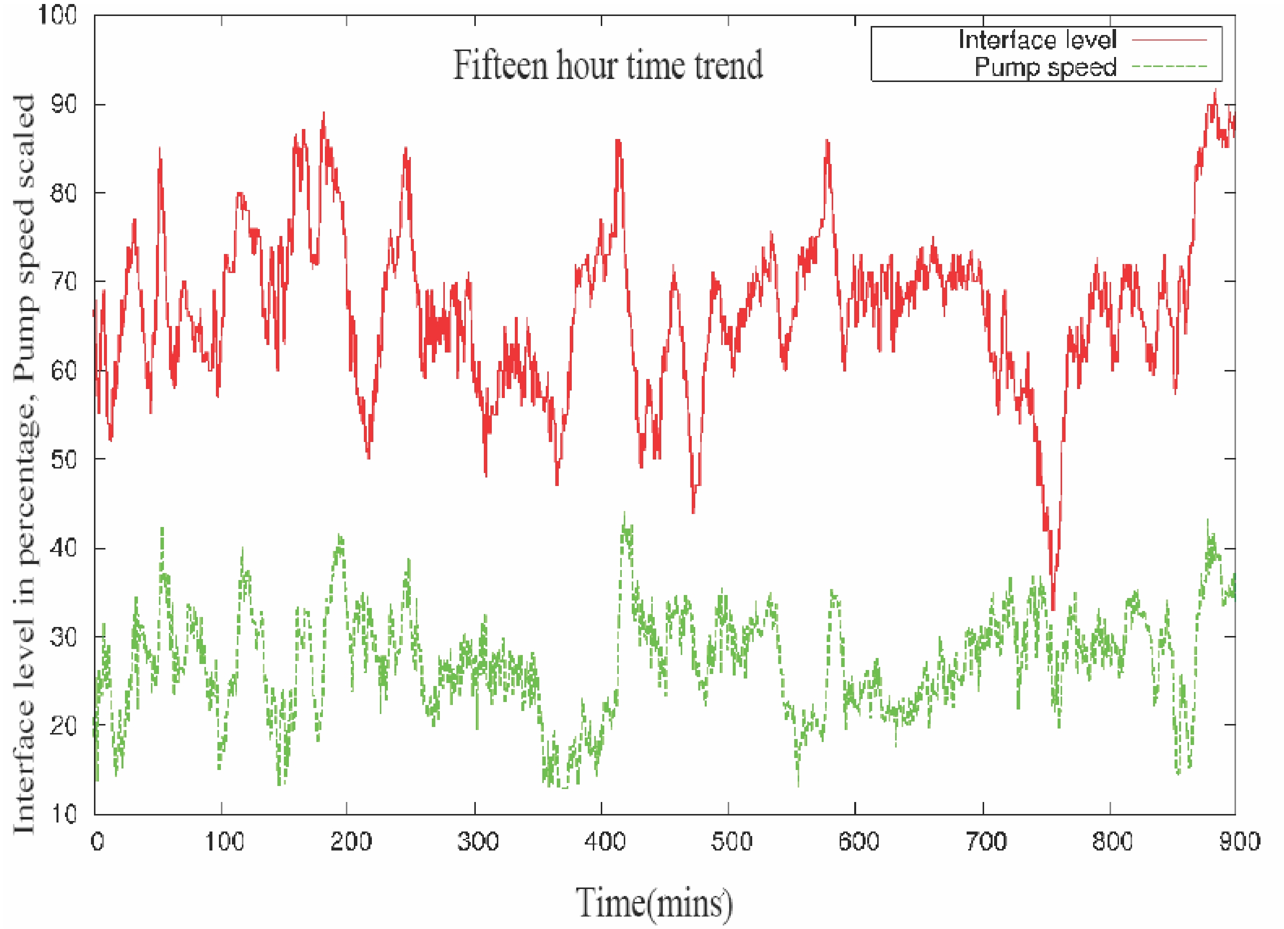
# Problem Description – Interface video

- In the absence of measurements, operators watch the side glass video and adjust the tailings pump speed manually



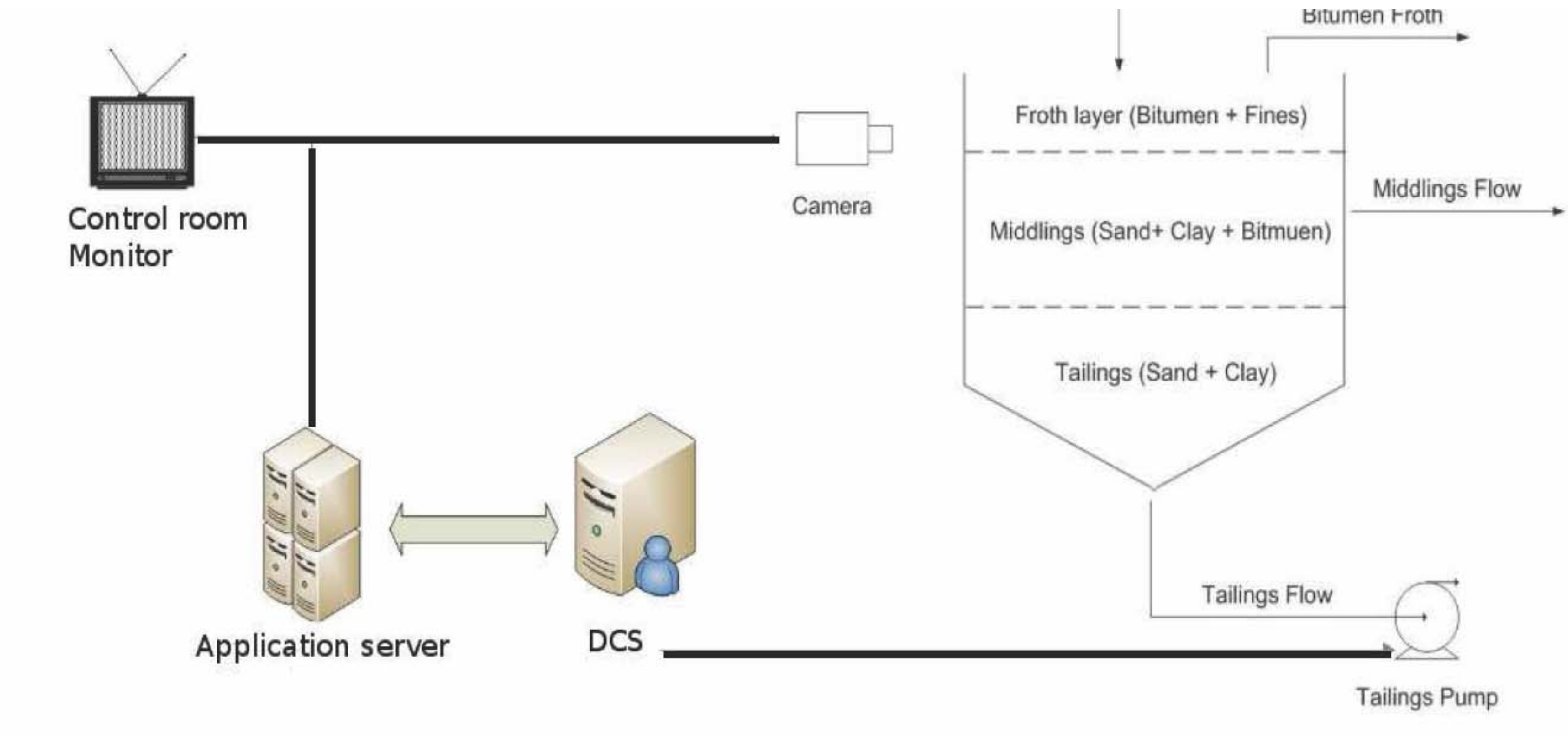

A video clip from sight glass camera

# Problem Description – manual control




Manual control of interface level

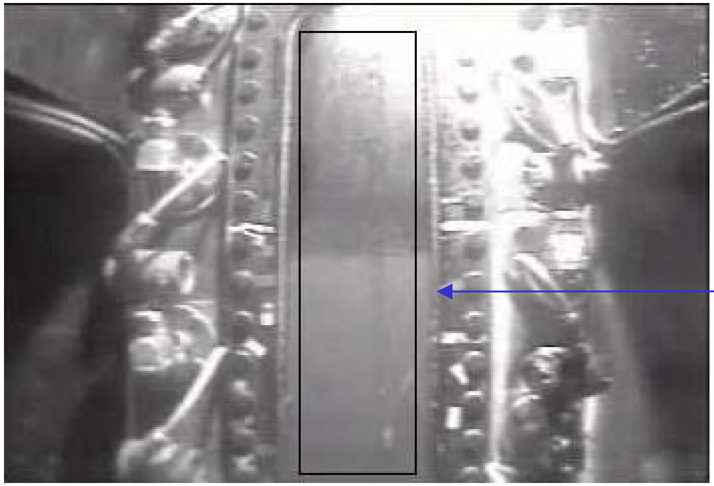
# Problem Description – Desired control system




The desired automatic control system using image sensor estimates for use in the feedback loop

# Interface level detection algorithm

- **Image ROI**:- Only the contents of this area in the image are processed.

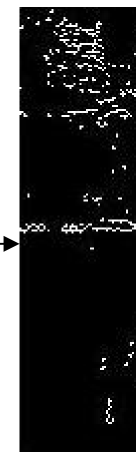


ROI: fixed

- As the interface level is mostly horizontal, *horizontal edge detection* is performed.

# Interface level detection algorithm – Edge detection

- Result of horizontal edge detection:-




- For robust tracking in the presence of spurious edges particle filtering methods are used

# Interface level detection algorithm
# Bayesian Filtering

- Bayesian filtering is a probabilistic framework for estimating the current state given all the observations.
- Two equations provide the basis of this framework:-
  - State equation $x_k = f\left(x_{k-1}\right) + w_{k-1}$
  - Observation equation $Z_k = g\left(x_k\right) + v_k$

  Where $w_{k-1}$ and $v_k$ are assumed to be white noise sequences, $x_k$ is the current state and $z_k$ is the current observation.
- The problem is to find the pdf (called the posterior) :-

$$p\left(x_k \mid Z_1, Z_2, \ldots, Z_k\right)$$

# Bayesian filtering -- Solutions to the recursive set

- When the state and the measurement equations are linear and if the noise terms and the prior are assumed to be *Gaussian*, the integral can be evaluated analytically and the recursive solution is given by the ***Kalman filter algorithm***

- In the general case the integration cannot be performed analytically (because the process may be non-linear and/or the noise is non-Gaussian). In such cases an approximate solution is obtained using *Monte Carlo methods* –these methods are collectively called ***particle filters***

# Interface level detection algorithm -- Particle filters

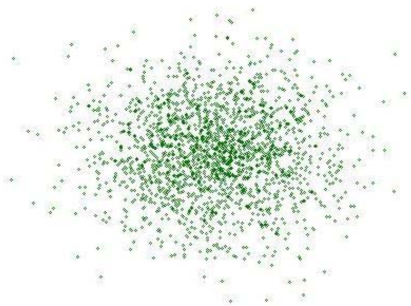
$$p(x_k \mid Z_1, Z_2, \ldots Z_{k-1}) = \int_{x_{k-1}} p(x_k \mid x_{k-1}) p(x_{k-1} \mid Z_1, Z_2, \ldots, Z_{k-1}) dx_{k-1}$$

Intractable

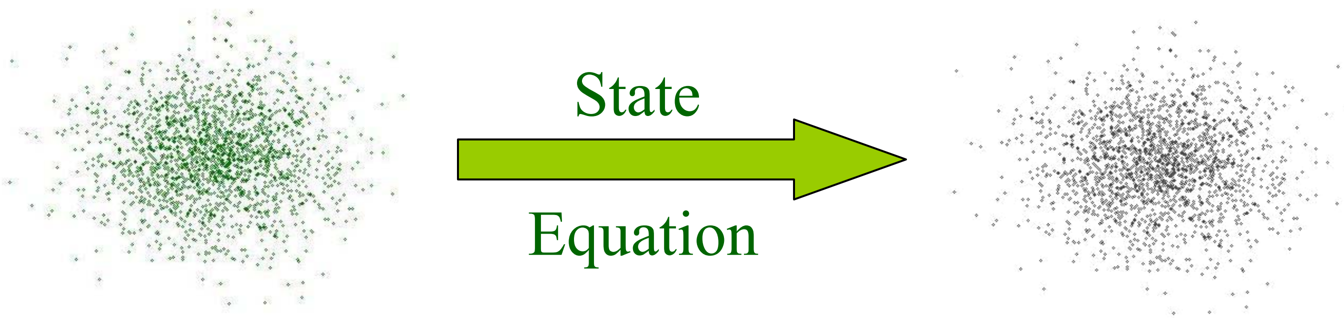
$$p(x_{k-1} \mid Z_1, Z_2, \ldots, Z_{k-1})$$

Draw

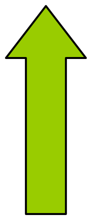
samples



# Particle filters – SIR Filter




$$p\left(x_k \mid Z_1, Z_2, .., Z_{k-1}\right)$$



$$p\left(x_{k-1} \mid Z_1, Z_2, ..., Z_{k-1}\right)$$

$$p\left(x_k \mid Z_1, Z_2, .., Z_k\right) = K \cdot p\left(Z_k \mid x_k\right) \cdot p\left(x_k \mid Z_1, Z_2, .., Z_{k-1}\right)$$

# State model

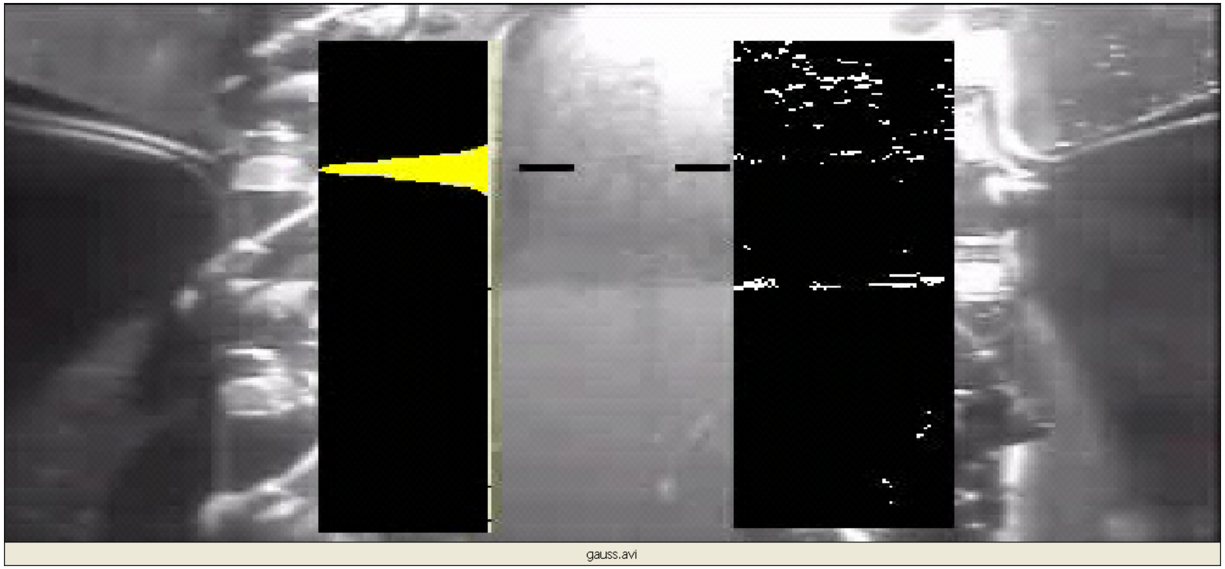
$$x_k = x_{k-1} + w_{k-1}$$

$x_k$ -- Current interface level (in pixels)

$w_{k-1}$ -- Gaussian white noise sequence with a small variance

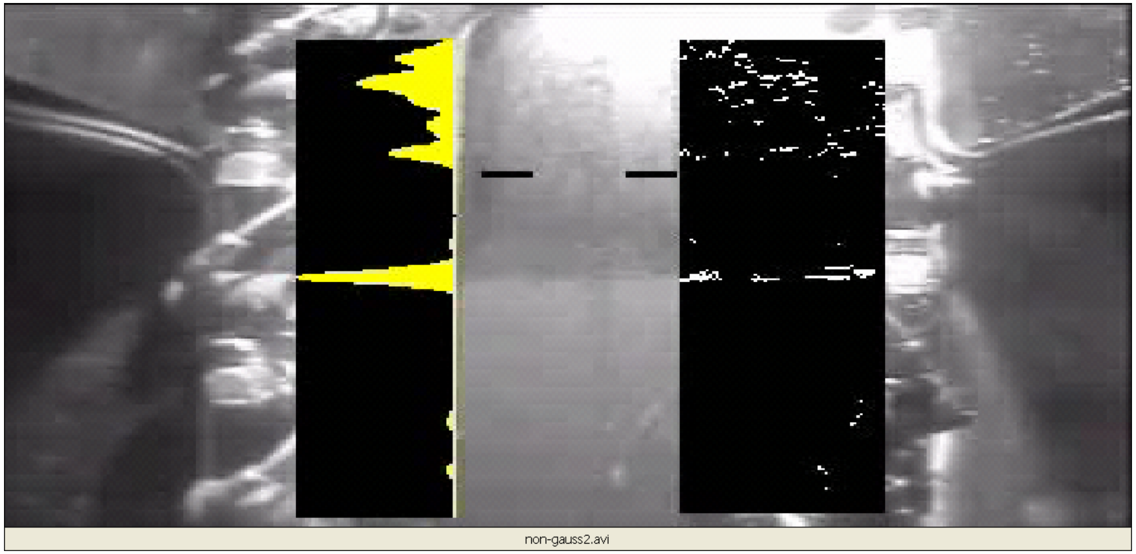
- Justifications
  - First principle model is difficult
  - Temporal continuity constraint when frame rate is high

# Results –Gaussian model



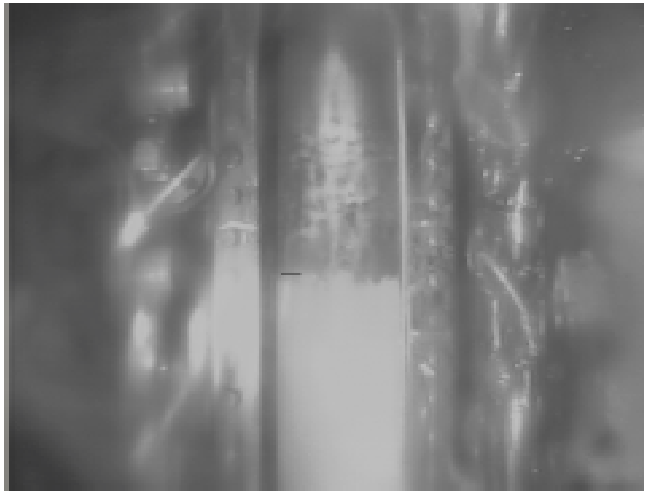

Disadvantage :- A Gaussian likelihood model only supports a unimodal posterior, hence the tracker is distracted by noise

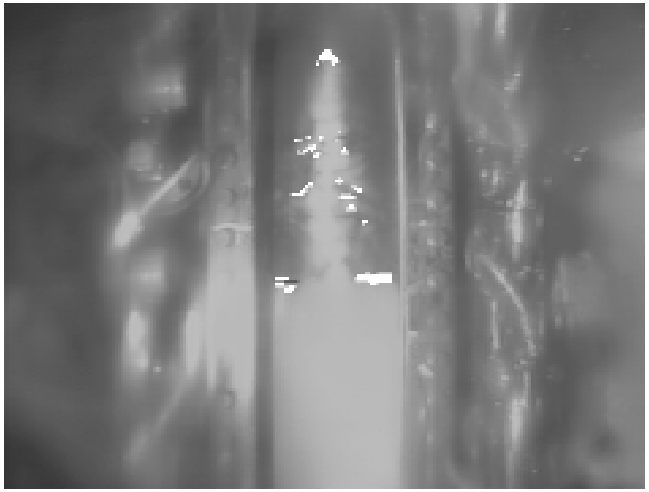
# Results –Non Gaussian model




***Advantage***:- **Multi-modal likelihood (and posterior), the tracker converges on the interface level after initially being distracted.**

# Results – Real time images





# Interface level quality estimation

Fines situation

Support of posterior p.d.f.

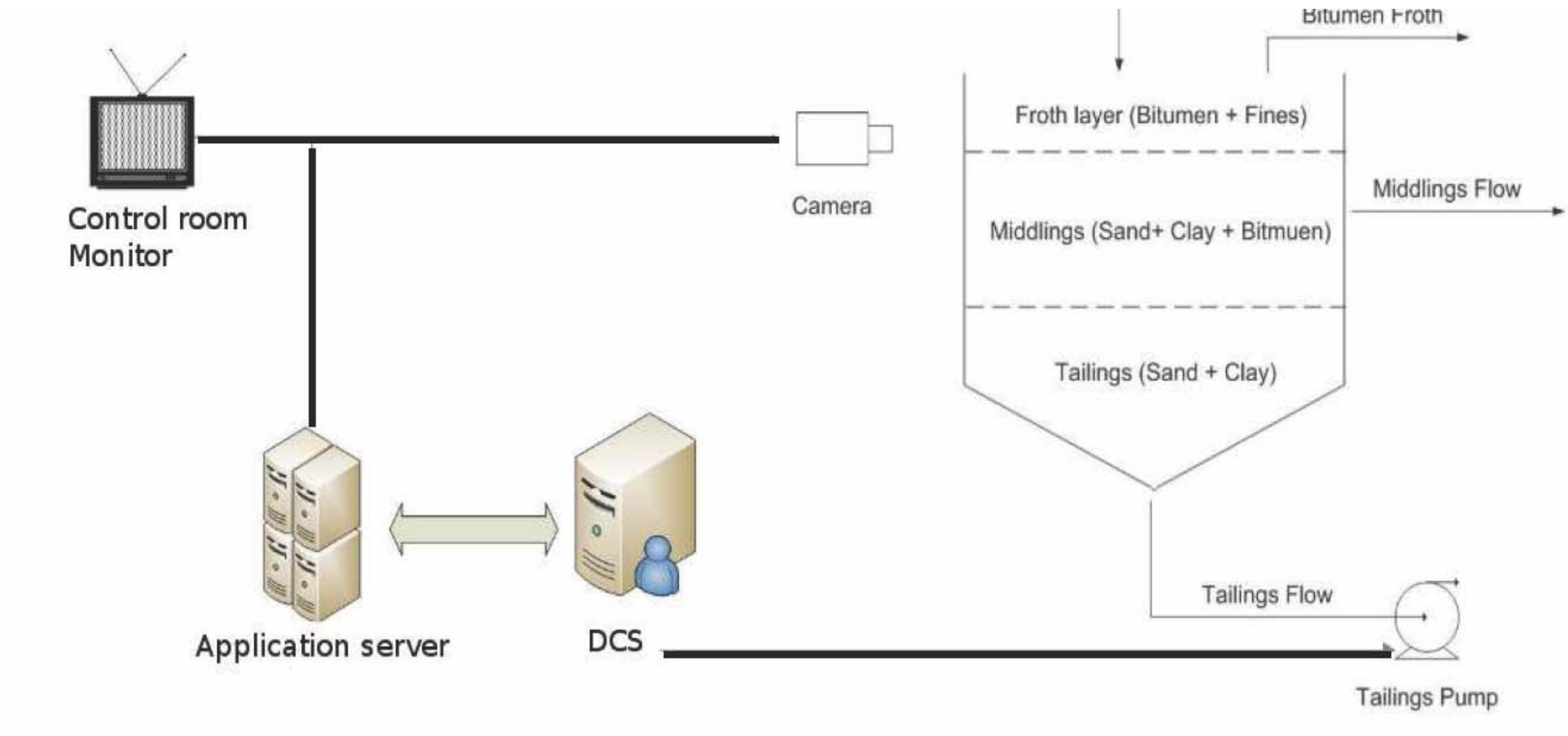
# Interface level quality estimation

(a) spread = 6

(b) spread = 13

(c) spread = 30

# Problem Description – Desired control system

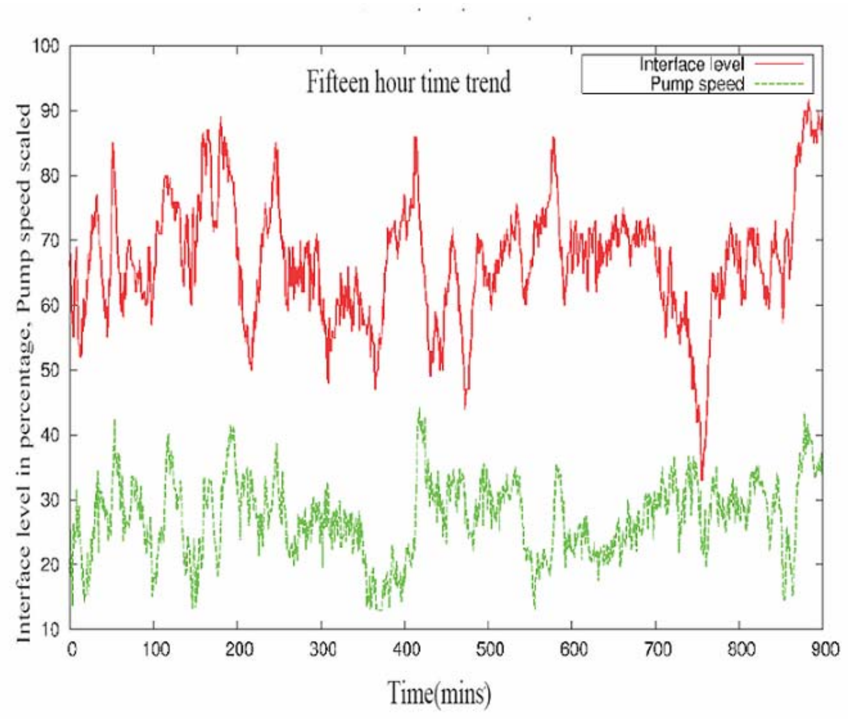



The desired automatic control system using image sensor estimates for use in the feedback loop

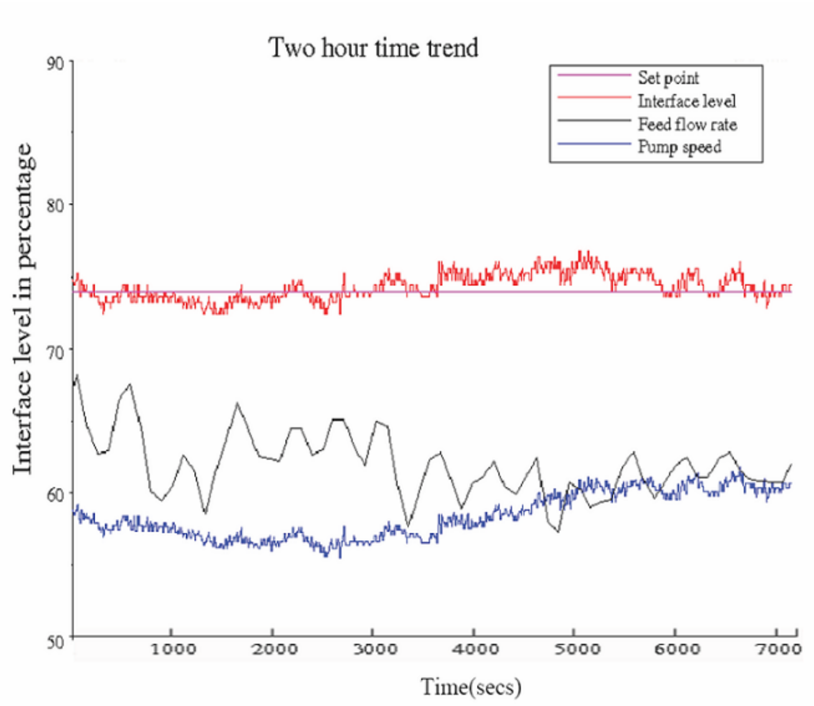
# Software and Hardware

- Intel Image Processing Primitives (IPPL) 5.1 for Windows
- Intel Open Computer Vision Library (Intel OpenCV)
- Matrox Imaging Library
- Matrox Meteor II frame grabber card

# Closed loop control results




Manual control




Automatic control using
Image sensor estimates

# Concluding Remarks

- Bitumen-froth and Middling's interface is detected using a Particle filtering algorithm.
- The developed algorithm is robust to lighting changes.
- Quality estimates of the interface level are also computed to handle process abnormalities.
- Results show that variance in the interface level is reduced significantly when the interface level estimates from the image based sensor are used in the feedback loop.

# Future work

- Image-based sensor for line 7. This has 3 sight glasses. Preliminary results will be shown.


# Acknowledgements

- G. Brandt, M. Collina, B. Doucette (all at Suncor) for technical help

# THANK YOU