# Using object detection to measure excavator teeth length

Andrés Martinez (andres.martinez@services.mss.pe), Marco Portocarrero (marco.portocarrero@ms4m.com)

MS4M Research and Development Department - Lima, Peru

## Motivation

- Measuring the teeth length of excavators is a manual process that involves stopping mining operations, which means losses in revenue.
- Automatic measurement could help find abnormal behaviours in teeth wear easier and faster.
- There is little work published on computer vision used in excavators, specially in monitoring teeth length.

## Data Acquisition

Data acquisition consisted in obtaining images from the arm of an excavator using a thermal camera of 320x256 pixels of resolution, as seen in fig. 1.

Figure 1:Installation of thermal camera in metal chassis in excavator

An object detection model was used to get the dimensions of the teeth from images, as in [2]. Model training consisted of these steps:

- Obtain images from videos, choose the images where multiple (more than 3) teeth are visible.
- 90/10 split of the dataset consisting of 700 labeled images.


Figure 2:Labels used for training the object detection model.

## Object Detection Results

The trained model was tested with images unrelated to the dataset used for training, using a tool [1] to calculate the mAP. The mAP was measured for 150 images, resulting in 87% mAP.

## Data Processing

The sampling rate of the model is 5 measurements every second, there is a wide range of teeth length data, as shown in fig. 3. Holt's Exponential smoothing filter was applied to obtain a constant measurement, given by:

$$\begin{aligned} s_t &= \alpha l_t + (1-\alpha)(s_{t-1} + b_{t-1} \\ b_t &= \beta(s_t + s_{t-1}) + (1-\beta)b_{t-1}, \end{aligned} \quad (1)$$

where $l_t$ is the length detected by the model, $s_t$ and $b_t$ are the level and trend respectively at time $t$, $\alpha$ and $\beta$ are parameters. The forecast, $L$, at time $t+1$ is given by:

$$L_{t+1} = s_t + b_t \quad (2)$$

The information the client is given is the forecast. A moving average filter was also considered, however it better results were found with Holt's filter until a moving average with 9 000 terms was considered which involved too many numbers saved in memory and took a significantly longer to compute compared to Holt's filter.

## Measurements

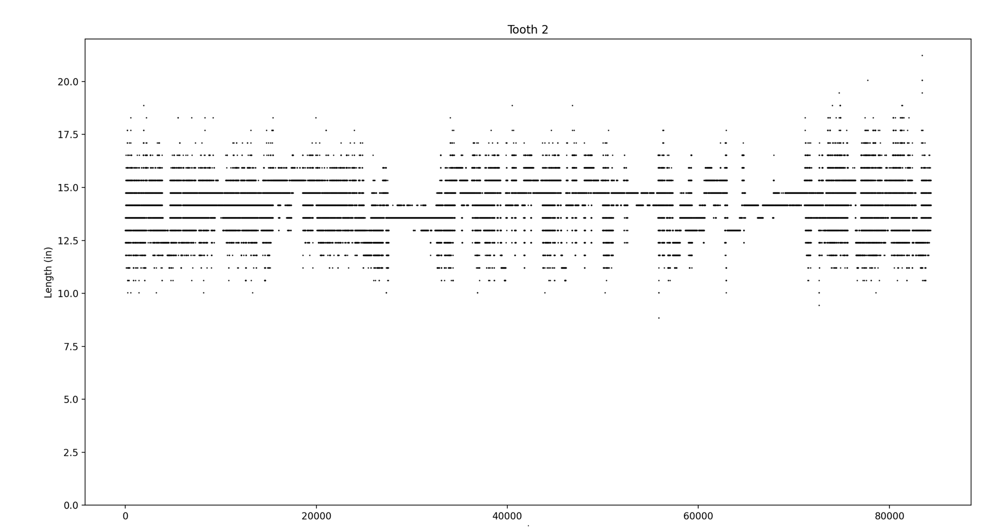


Figure 3:Spread plot of raw measured heights of the detection boxes for tooth 2 during an entire day.

A vast variance in the data obtained can be seen in fig. 3. For this reason we apply Holt's smoothing filter to the data obtained, as well as to be able to tell the downwards trend of the data.

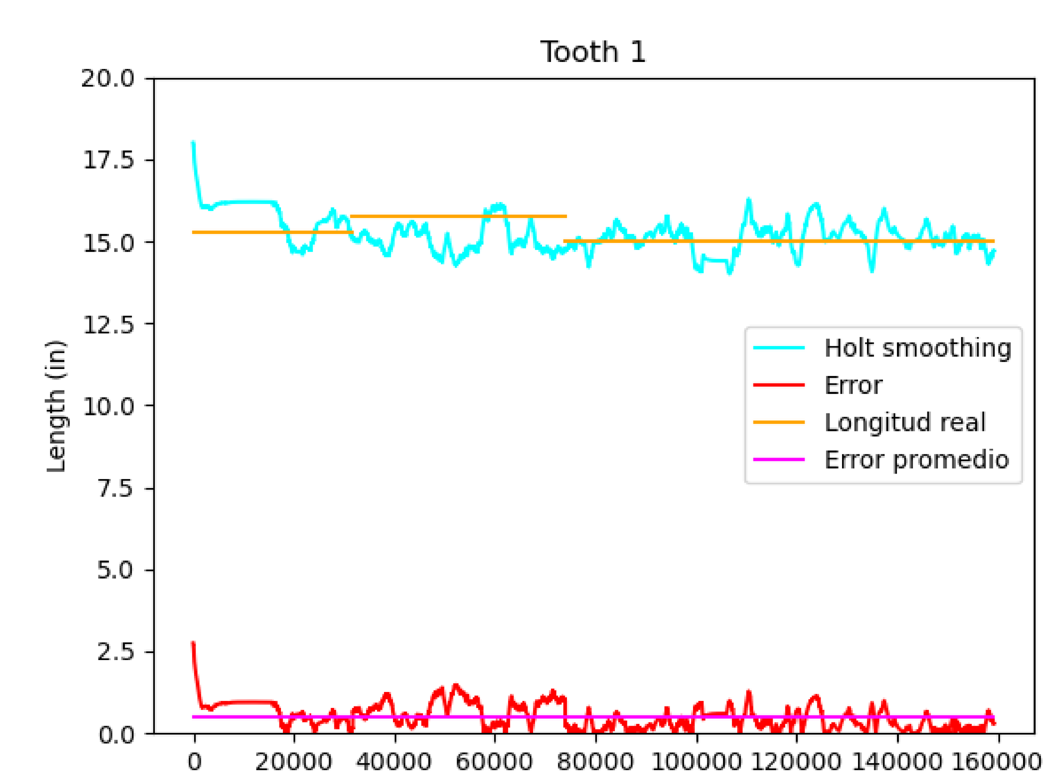


Figure 4:Measurements after applying Holt's Smoothing to raw data obtained from 2 days for tooth 2, against the real measurement given on the day, the average error is 0.5 inches.

According to the client, an error of ±2 inches is acceptable, while an error within ±1 inch is considered outstanding. The errors calculated for all teeth using Holt's filter are all within one inch of the real measurements counting both days.

## Conclusion & Future Work

- Using a tool [1] we measured the precision for our trained model, resulting in 87% mAP. The train/test split worked well, resulted in low overfitting.
- Holt's smoothing filter was easy to set up and it allowed for one continued feed, as well as to minimize up to ±1 inches in error.
- 87% mAP in the object detection model was enough to achieve an accurate measurement, as shown in fig. 4.
- Further tests with different types of excavators and teeth would be necessary to verify if the method can be applicable to the general problem.
- Kalman filter approaches could also be applicable to this problem.

## References

[1] Rafael Padilla, Wesley L. Passos, Thadeu L. B. Dias, Sergio L. Netto, and Eduardo A. B. da Silva.
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[2] Hooman Shariati, Anuar Yeraliyev, Burhan Terai, Shahram Tafazoli, and Mahdi Ramezani.
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