PigVision

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On-line monitoring of slaughter pigs: PigVision

Innovation project led by Danish Pig Production:
- Danish Institute of Agricultural Sciences
- Videometer (external assistance)
- Skov A/S
- LIFE, IPH, Production and Health

Continuous monitoring of daily gain while still in herd:
- Dynamic Linear Models
- Chance of interference in the fattening period
- Adaptation of delivery policy

PigVision: Principles

A camera is placed above the pen. In case of movements a series of pictures are recorded and sent to a computer.

The computer automatically identifies the pig (by use of a model) and calculates the area (seen from above).

If the computer doesn’t believe that a pig has been identified, the picture is ignored.

The area is converted to live weight (using a model).

Through many pictures, the average weight and the standard deviation are estimated.

Figure by Teresia Heiskanen
What is online weight assessment used for?

Continuous monitoring of gain.
Collection of evidence about growth capacity (learning)
Adaptation of delivery policies depending on:
• Whether the pigs grow fast or slowly
• Whether the uniformity is small or big
• Whether a new batch of piglets is ready
• Prices
Direct advice about pigs to deliver

On-line weight assessment
Pen with \( n \) pigs is monitored. No identification of pigs.
At any time \( t \) we have:
\[
g(t) = m(t) + e_t, \quad t = 1, \ldots, n
\]
where:
- \( m(t) \) is the observed live weight of pig \( i \)
- \( e_t \) is the true live weight of pig \( i \)
\( e_t \sim N(0, \sigma^2) \) is the measurement error

The precision \( 1/\sigma^2 \) is assumed known.

The general (multivariate) Dynamic Linear Model

Chapter 8, Section 8.4:
Observation equation:
\[ y_t = \theta_t + e_t \]
System equation:
\[ \theta_t = G_t \theta_{t-1} + w_t \]
The parameter vector \( \theta_t \) is sequentially estimated as observations are done.
A dynamic linear weight model, I

Known average herd specific growth curve:

\[ \bar{y}(t) \]

True weights at time \( t \) distributed as:

\[ w_i(t) \sim N(\bar{y}(t)L, \sigma_L^2) \]

where \( L \) is a scaling factor representing the traits of the pigs currently occupying the pen.

The scaling factor \( L \)

In principle unknown and not directly observable

Initial belief: \( L = 1 \)

The belief is updated each time we observe a set of live weights from the pen.

Let \( L \approx N(1, \sigma_L^2) \) be the true scaling factor:

Then

\[ w(t) = (\sum_i w_i) / n \]
\[ \bar{w}(t) = \bar{y}(t)L + e(t) \]

Observation & system equation 1

Full observation equation for mean:

\[ \bar{w}(t) = \bar{y}(t)L + e(t) + \varepsilon_t \]

Auto-correlated sample error (system eq.):

\[ e(t) = \alpha e(t-1) + \eta_t \]
Observation & system equation 2

Far more information available from the observed live weights $\xi_1(t), \ldots, \xi_n(t)$
Sample variance not normally distributed.
Use the 0.16 sample quantile:

$$\hat{\omega}_{0.16}(t) = \bar{y}(t)L + \varepsilon(t) - \rho(t) + \eta$$

The symbol $\rho(t)$ is the standard deviation of the observed values. System equation:

$$\rho(t) = \frac{1}{1-t} \rho(t-1)$$

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Full equation set

**Observation equation:**

$$\begin{bmatrix} \hat{\xi}(t) \\ \hat{\omega}_{0.16}(t) \end{bmatrix} = \begin{bmatrix} \hat{y}(t) & 1 & 0 \\ \hat{y}(t) & 1 & -1 \end{bmatrix} \begin{bmatrix} L \\ \varepsilon(t) \\ \rho(t) \end{bmatrix} + \begin{bmatrix} \xi_i \\ \eta_i \end{bmatrix}$$

**System equation:**

$$\begin{bmatrix} L \\ \hat{\varepsilon}(t) \\ \hat{\rho}(t) \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} L \\ \varepsilon(t-1) \\ \rho(t-1) \end{bmatrix} + \begin{bmatrix} 0 \\ \eta_i \end{bmatrix}$$

Each time $\hat{\xi}(t)$ and $\hat{\omega}_{0.16}$ are observed, the estimates of $L$, $\hat{\varepsilon}(t)$ and $\hat{\rho}(t)$ are updated.

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Learning, permanent growth capacity

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Learning: Homogeneity (standard deviation)