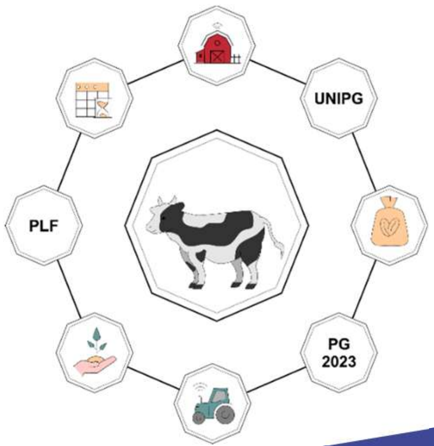
UNIVERSITÀ DEGLI STUDI DI PERUGIA

Impact of PLF in farm animal welfare

Using PLF in extensive sheep and goat production



Severiano R Silva

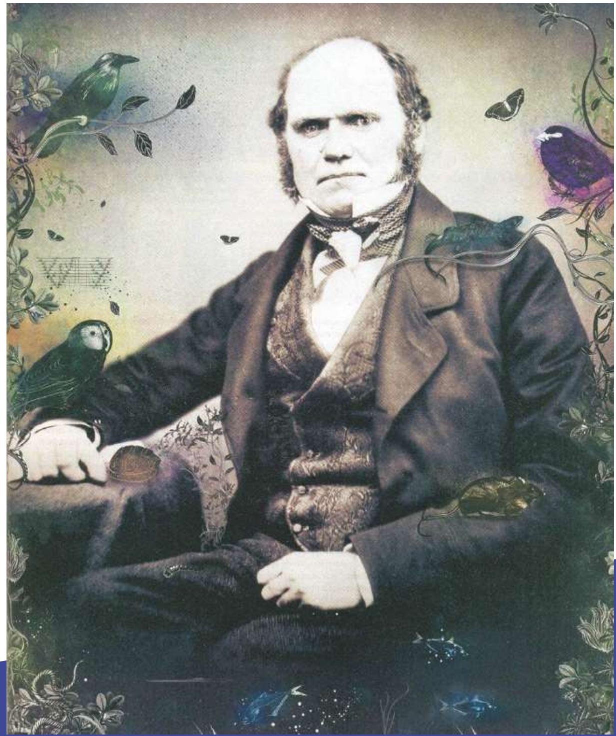
CECAV ANIMAL AND VETERINARY RESEARCH CENTRE
AL4Animals
utad

XVII century - René Descartes (1596-1660) in his conception, animals had no soul, and as such there was not even the possibility of them feeling pain.

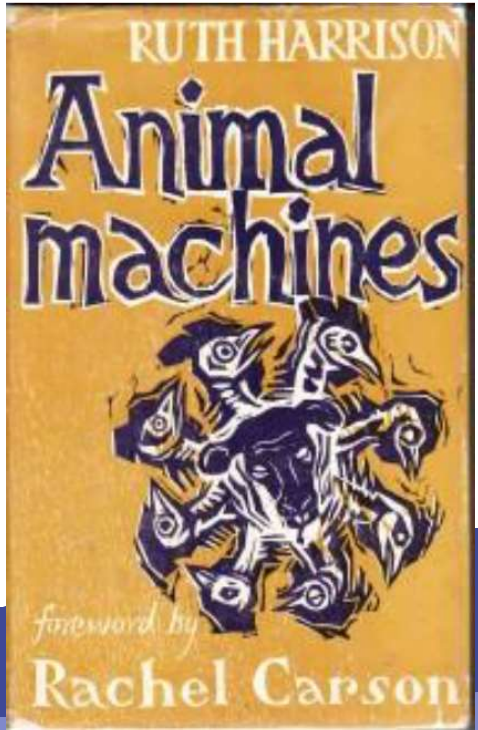
18th century - Philosopher Jeremy Bentham, in 1789. It doesn't matter if animals are capable of thinking or not. What matters is that they are capable of suffering.

A.D. 1308
unipg
UNIVERSITÀ DEGLI STUDI
DI PERUGIA

19th century - Charles Darwin recognizes that all animals feel pain and suffering in a similar way.



1964 - book “Animal Machines: The New Factory Farming Industry” (Ruth Harrison). It has been considered a catalyst for changes in the field of farm animal welfare.



1965 – Brambell report

Report of the
Technical Committee to Enquire into the
Welfare of Animals kept under
Intensive Livestock Husbandry Systems

Chairman: Professor F. W. Rogers Brambell, F.R.S.

Presented to Parliament by the Secretary of State for Scotland and the
Minister of Agriculture, Fisheries and Food
by Command of Her Majesty
December, 1965


The Five Freedoms
Freedom from - hunger & thirst
pain, injury & disease
fear & distress
discomfort
Freedom to - display natural behaviours

Tijdschr Diergeneeskd. 1979 Nov 15;104(22):898-900.

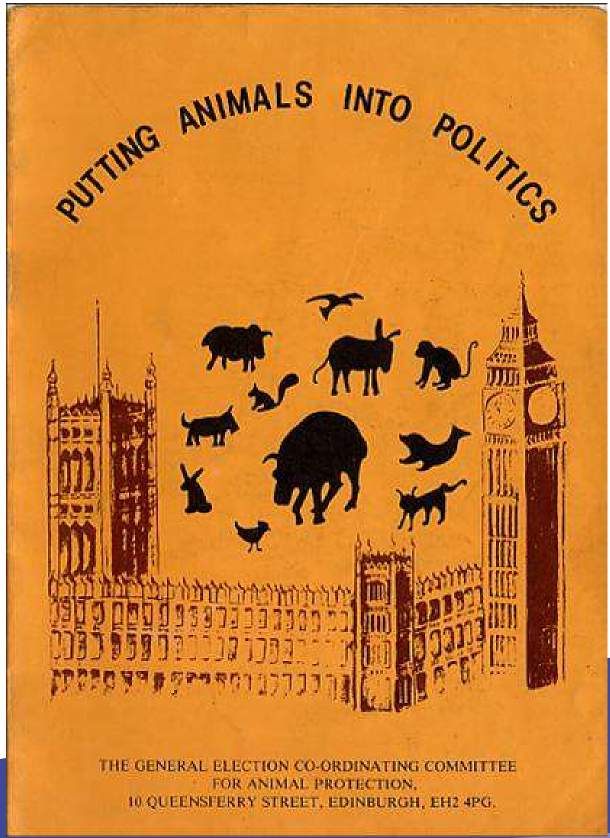
[First European Conference Welfare of Livestock Animals].

[Article in Dutch]

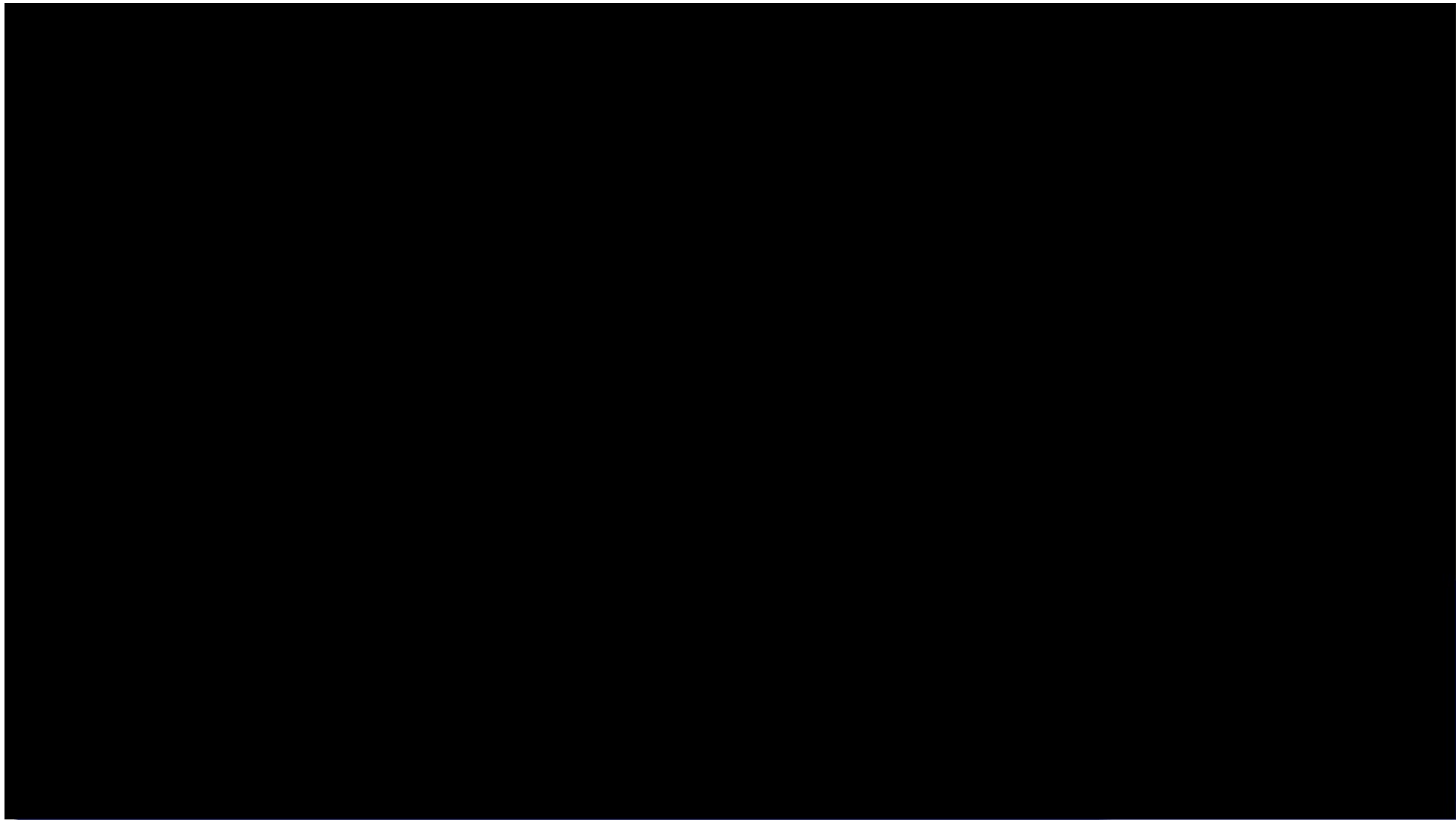
Wieringa HK.

PMID: 42166 [PubMed - indexed for MEDLINE]

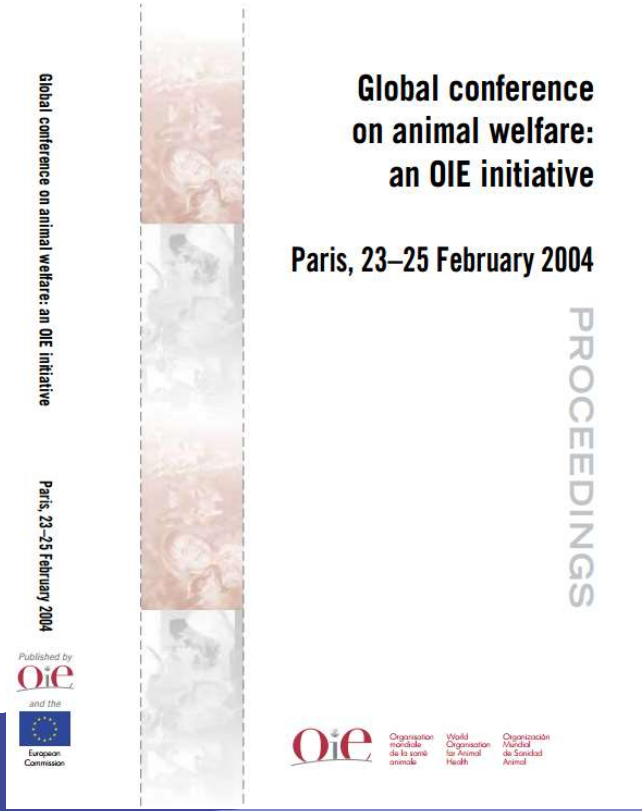
1979 - The first animal welfare manifesto for the 1979 general election.



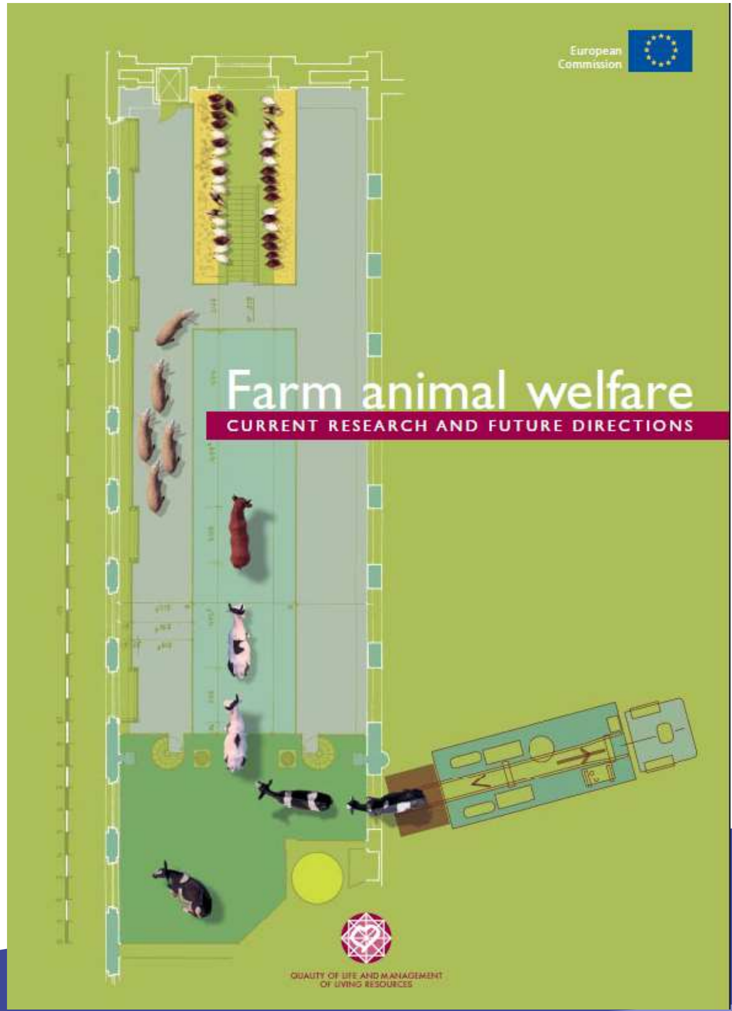
David Fraser



2004 – First global conference

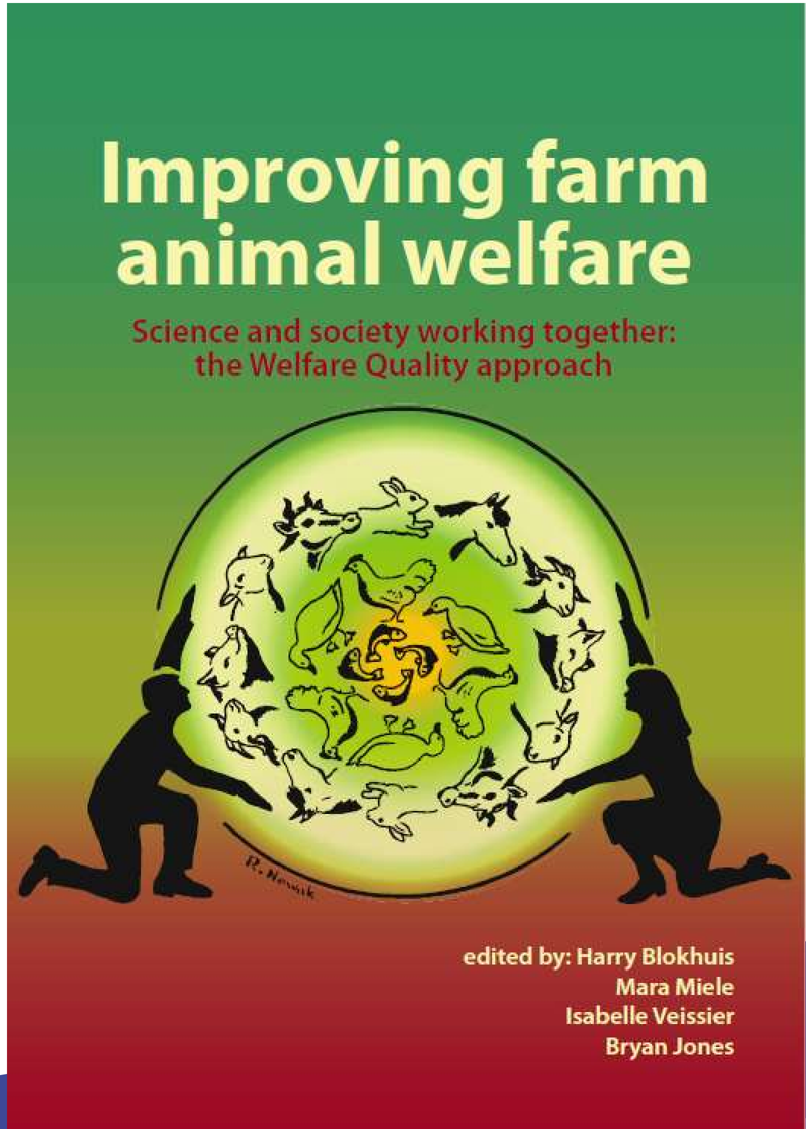


Farm animal welfare research I&D



A.D. 1308 unipg

UNIVERSITÀ DEGLI STUDI DI PERUGIA



Linda Keeling

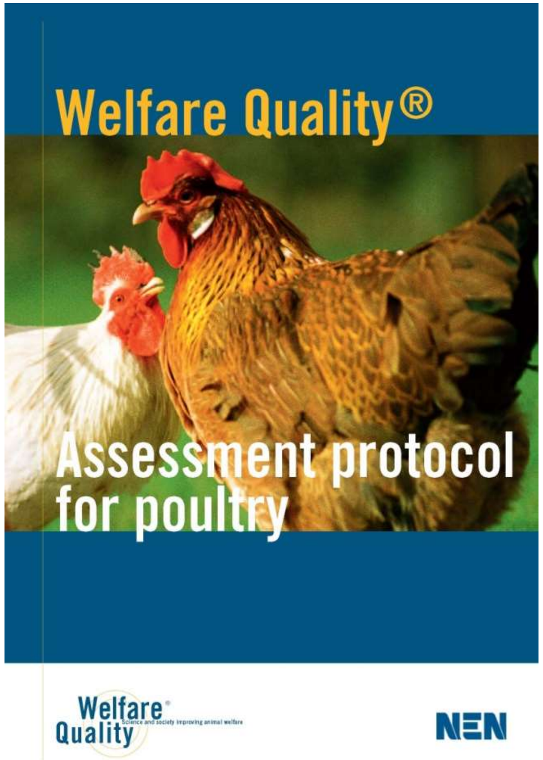
2008 - the Welfare Quality project re-elaborated the concept of the “Five Freedoms” (FAWC, 2009)

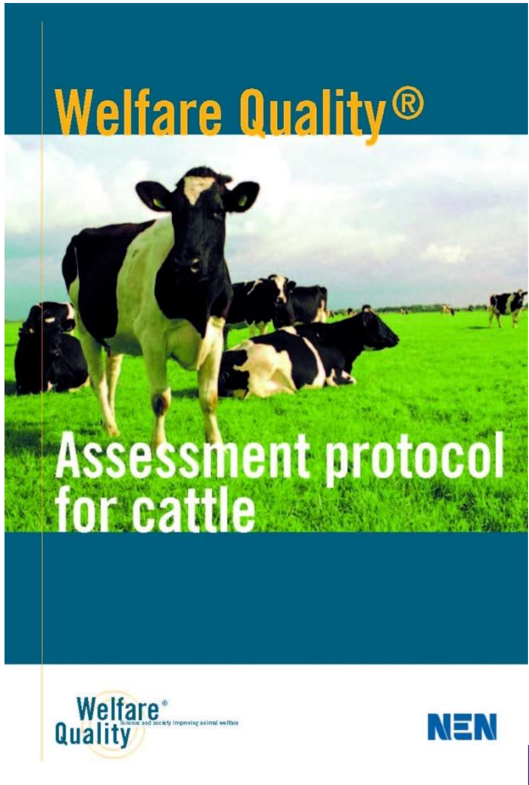
Welfare® Quality
Science and society improving animal welfare

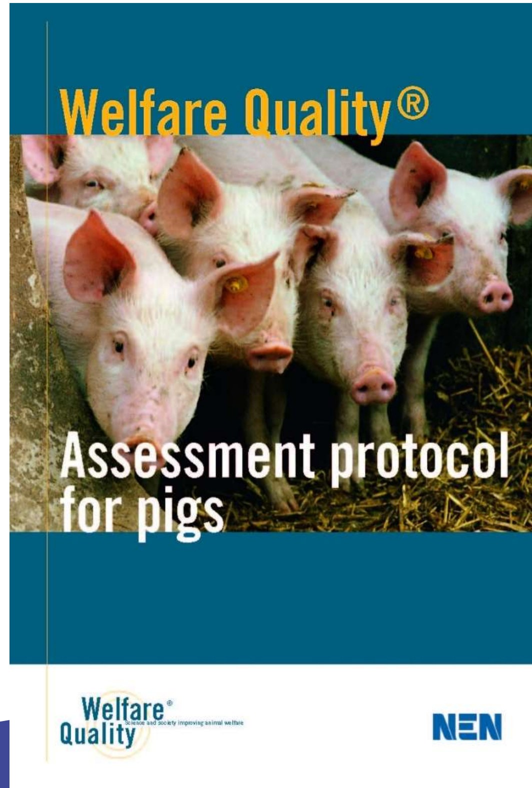
Science and society

Welfare Quality®: EU integrated project Food-CT-2004-506508

improving animal welfare in the food quality chain


Welfare Quality®
Assessment protocol
for poultry
Welfare Quality®
NEN


Welfare Quality®
Assessment protocol
for cattle
Welfare Quality®
NEN


Welfare Quality®
Assessment protocol
for pigs
Welfare Quality®
NEN

A.D. 1308 unipg
UNIVERSITÀ DEGLI STUDI DI PERUGIA

awin ANIMAL WELFARE INDICATORS

Search... GO

Home About Project Overview Project Team AW Science Hub Publications Learning Objects AWIN Events Employment Contact

About

- Goals and objectives
- Leadership
- Collaborations
- External Advisors
- Social Networks
- Press Room

Goals and objectives

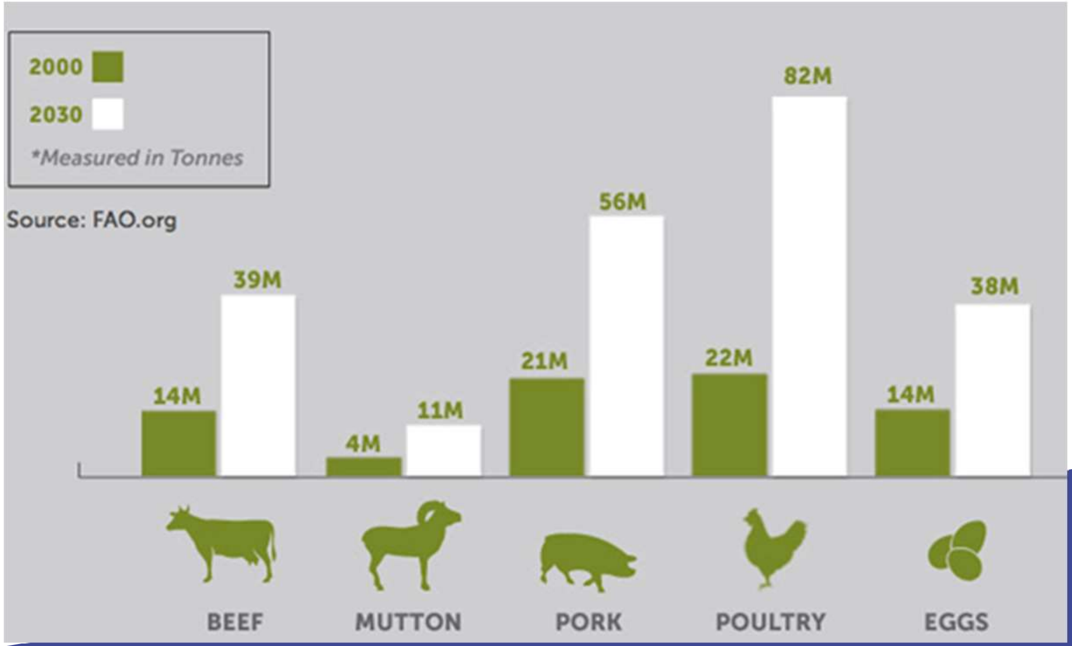
Our overall goal is to improve animal welfare by developing, integrating and disseminating information about animal welfare indicators.

We will have a special emphasis on the recognition and assessment of pain, as pain is an area that is frequently lacking from many animal welfare assessments and yet is often key when animal welfare problems arise.

Our research objectives to be carried out in our Workpackages (WP1, WP2, WP3) will focus on species that, although commercially relevant world-wide, have so far been overlooked in animal welfare assessments. These species are sheep, goats, horses, donkeys and turkeys.

Challenges for the Livestock Sector

Increase of the worldwide demand for animal products (meat, eggs, and milk) of 70% by 2050



Challenges for the Livestock Sector

Reducing the environmental impact

Challenges for the Livestock Sector

Global warning

Challenges for the Livestock Sector

Assuring the efficiency of the process


atf animal task force
A European Public-Private Platform

Vision Paper
towards European R&I
for a sustainable and competitive
livestock production sector in Europe

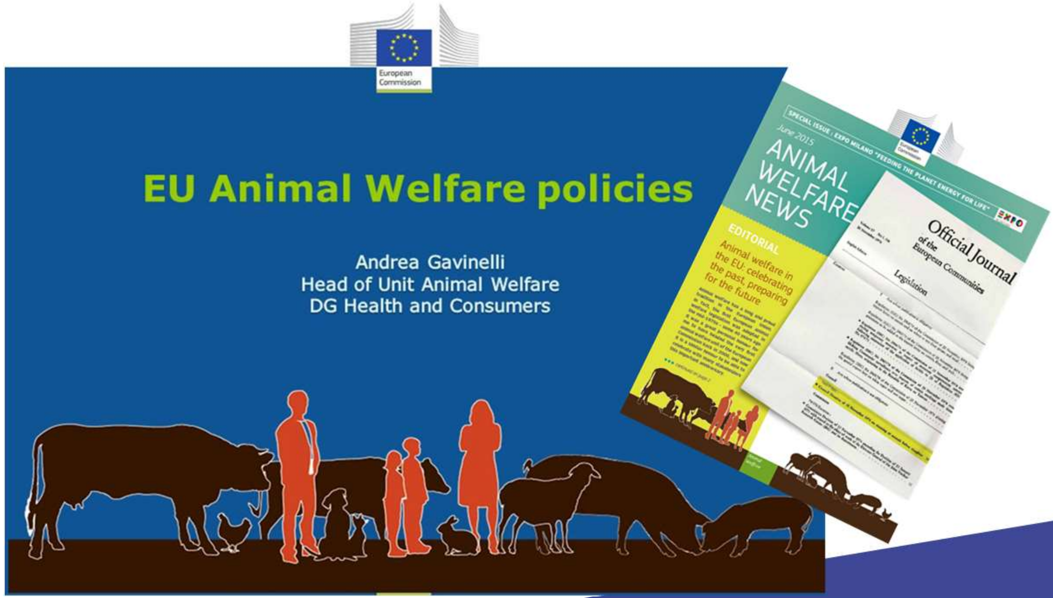
A framework for suggested priorities for R&I
within Horizon Europe

February 2019

Animal Task Force (2019)

Challenges for the Livestock Sector

Monitoring animal health and welfare



A.D. 1308
unipg
UNIVERSITÀ DEGLI STUDI
DI PERUGIA

Challenges for the Livestock Sector

Increase number of livestock

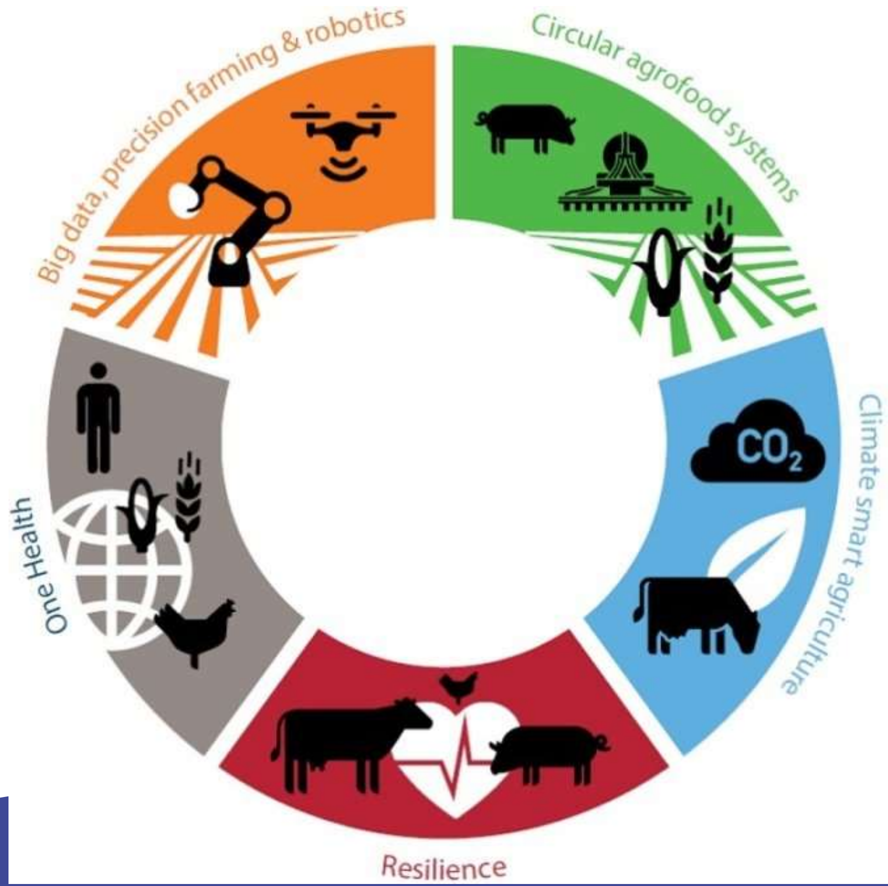
Decrease the number of farmers

Bigger herds per farmer ====== Impossible for farmers to follow all of their animals in a reliable way

Present and Future
sustainable and profitable livestock farming.

Five interrelated themes.

Climate smart livestock farming
Circular agrofood systems
One Health and livestock farming
Resilience in animals
Big data, precision farming & robotics

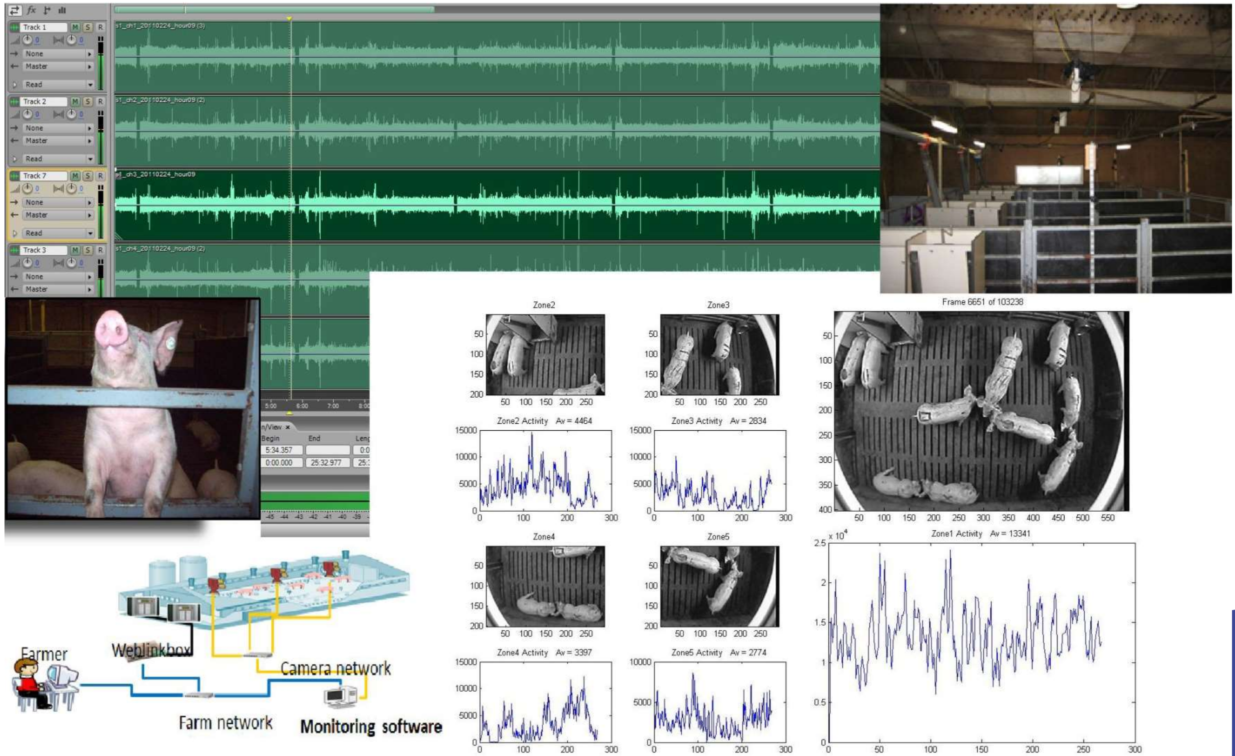


https://www.wur.nl/en/research-results/research-institutes/livestock-research/themes.htm

Health and welfare assessment in production environment

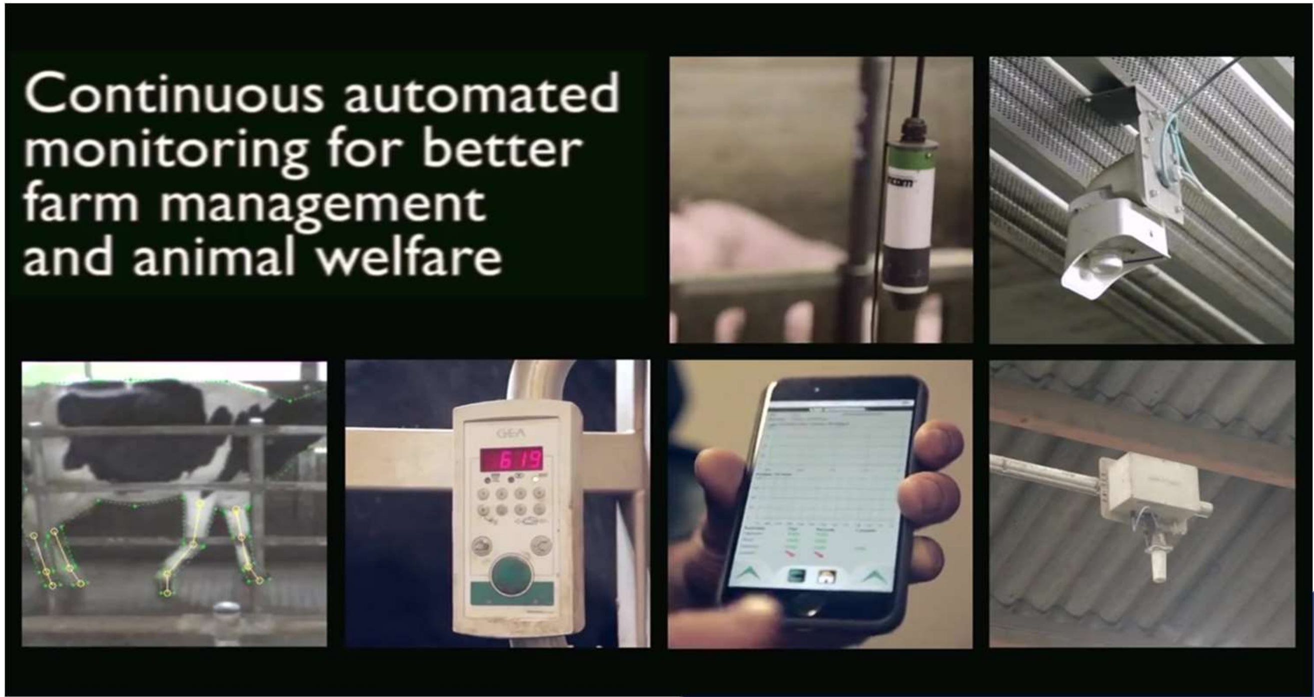
Berckmans (2013)

Possibility of integrating information into solutions that allow a continuous automated real-time monitoring of production, reproduction, health and welfare of animals



Berckmans (2013)

The monitoring can be done by camera and real-time image analyses, by microphone and real-time sound analyses, or by sensors around or on the animal as shown further



Berckmans (2017)

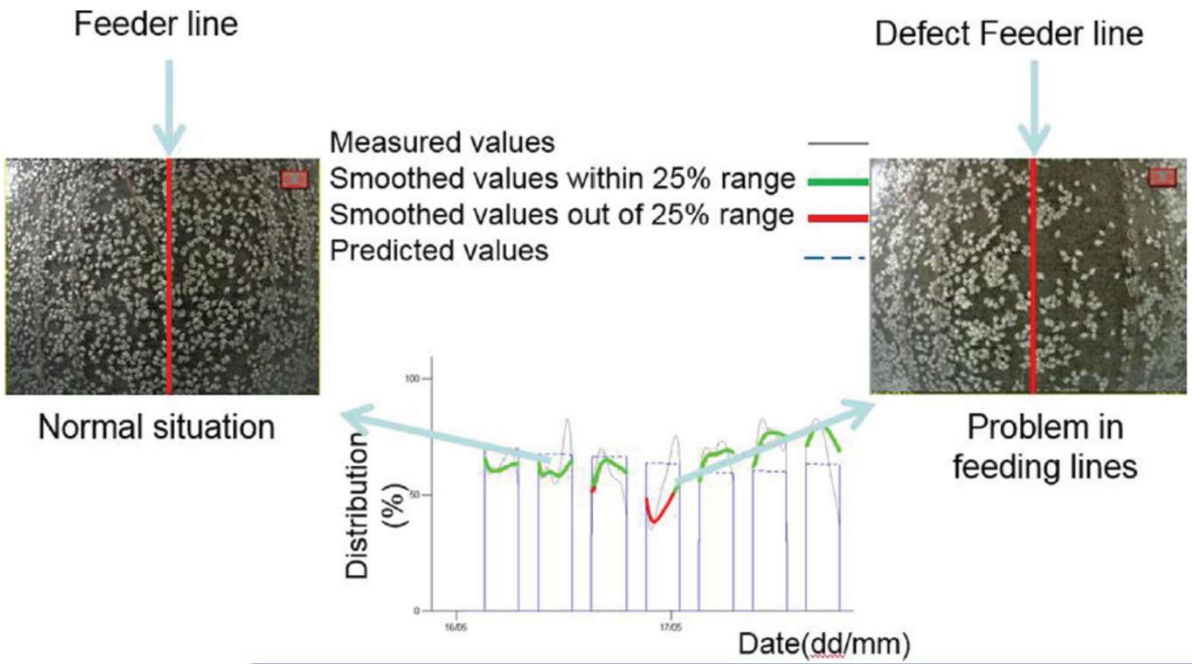
A.D. 1308
unipg
UNIVERSITÀ DEGLI STUDI
DI PERUGIA

Precision livestock farming (**PLF**) aims to offer a real-time monitoring and managing system for farmers.

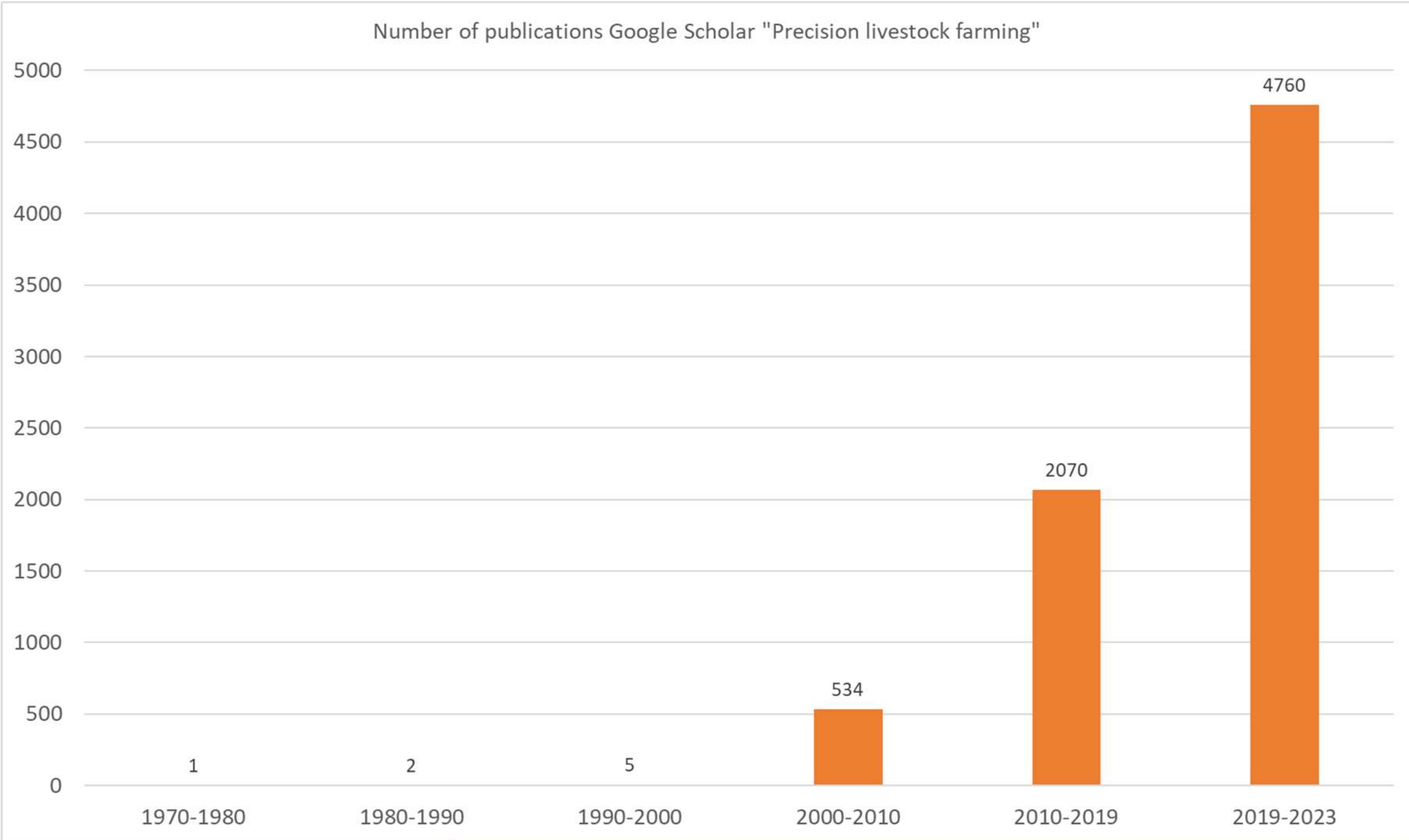
The aim of PLF is to manage individual animals by continuous real-time monitoring of health, welfare, production/reproduction, and their environmental impact (Berckmans, 2017).

Continuous means that PLF technology is measuring and analyzing every second, 24 h a day, and 7 d a week

Farmers get a warning when something goes wrong



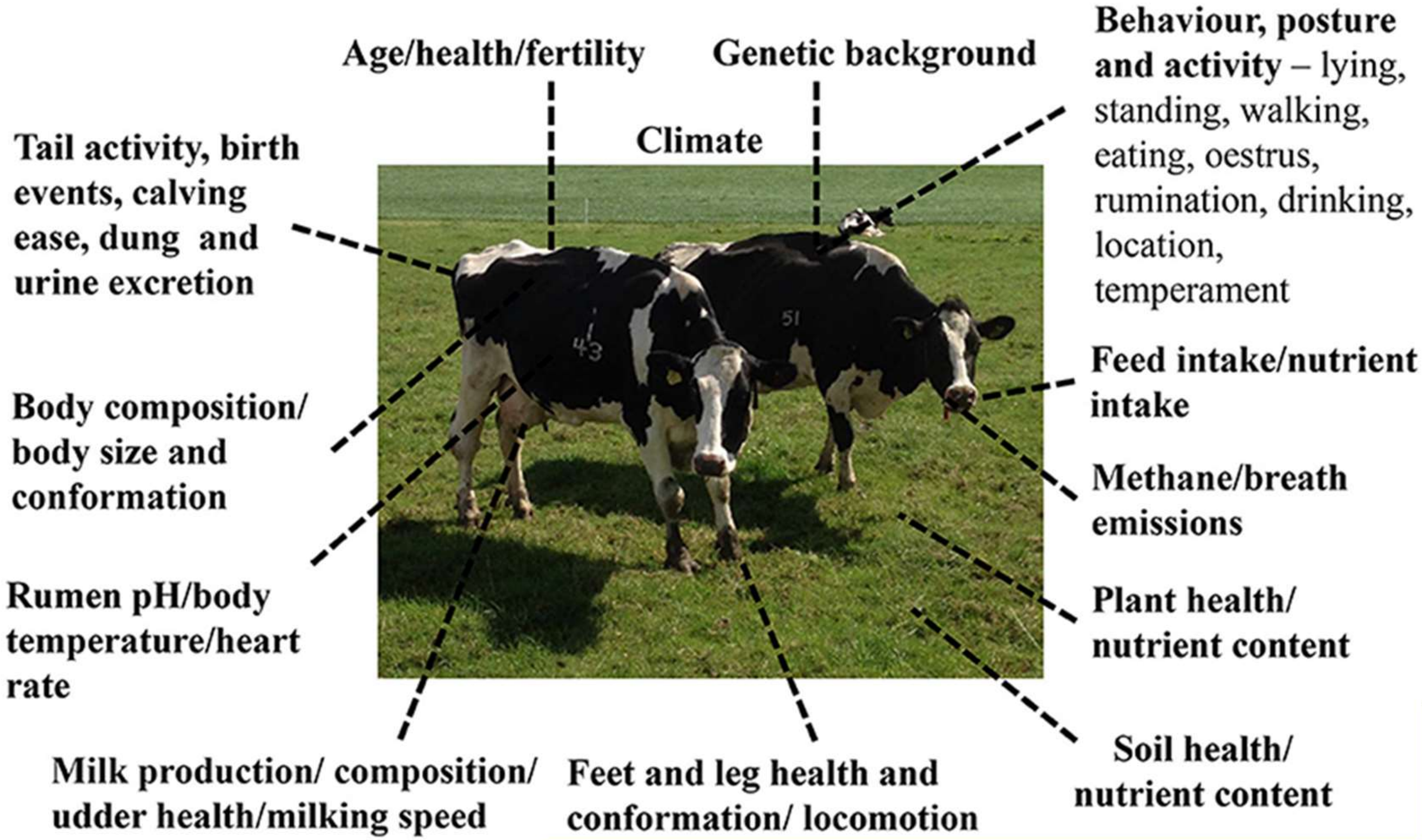
Berckmans (2017)



Number of publications Google Scholar "Precision livestock farming"
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
0
1
2
5
534
2070
4760
1970-1980
1980-1990
1990-2000
2000-2010
2010-2019
2019-2023


Precision Livestock Farming
(PLF)

Important issues in Dairy Cows



This is why Big Data is always present

Animal (2019), **13:7**, pp 1519–1528

Invited review: Big Data in precision dairy farming

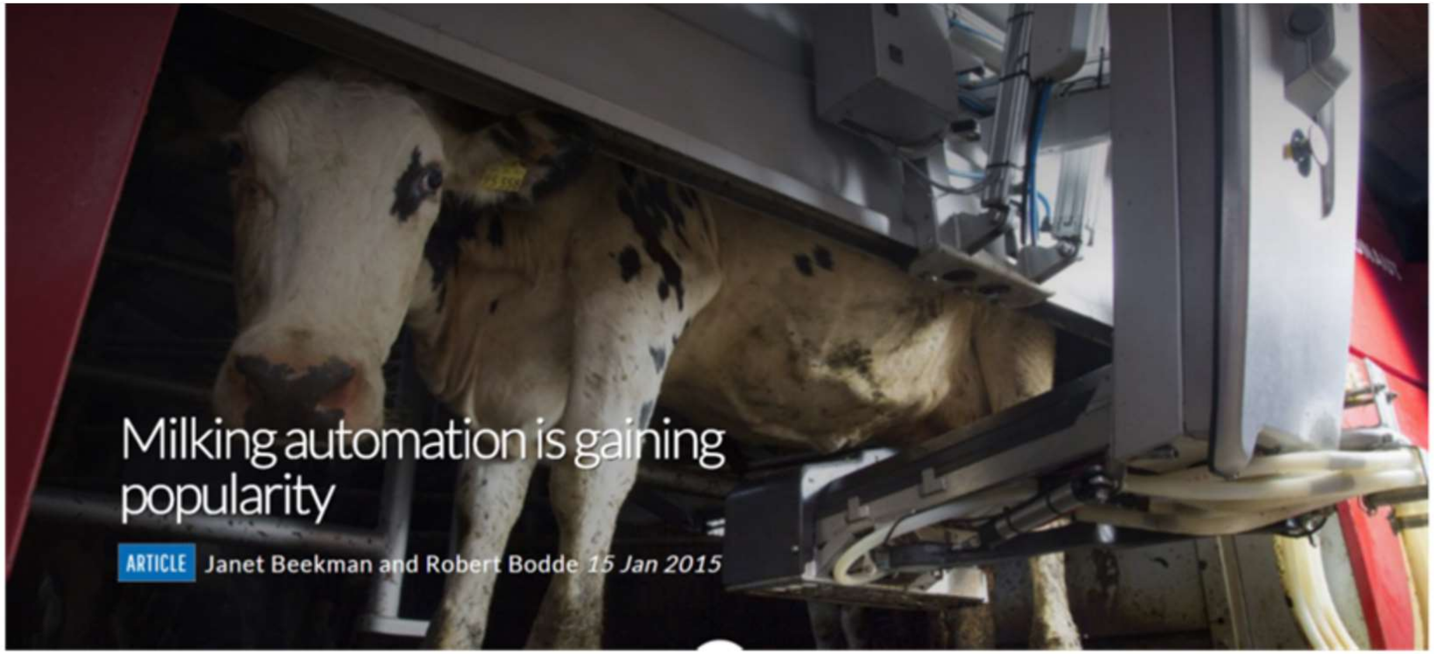
C. Lokhorst[1,2†], R. M. de Mol[1] and C. Kamphuis[1]

[1] *Wageningen Livestock Research, PO Box 338, 6700AH Wageningen, The Netherlands;* [2] *Van Hall Larenstein University for Applied Science, PO Box 1528, 8901BV Leeuwarden, The Netherlands*

Some examples of PLF use in dairy industry
Milking Robot - one of the earliest precision livestock farming developments

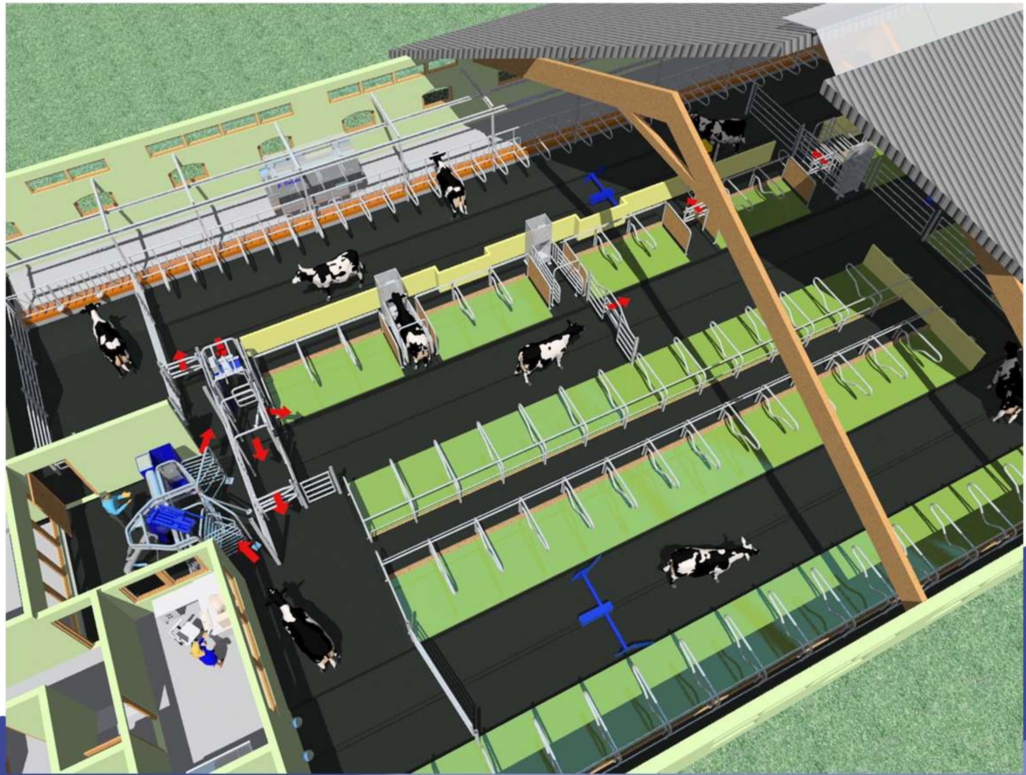
https://www.lely.com

Numerous changes to how the whole farm system is managed



In 2025 almost half of the dairy herds in north west Europe will be milked by robots.

Numerous changes to how the whole farm system is managed-
Barn design and traffic of the cows



Numerous changes to how the whole farm system is managed- Feeding distribution

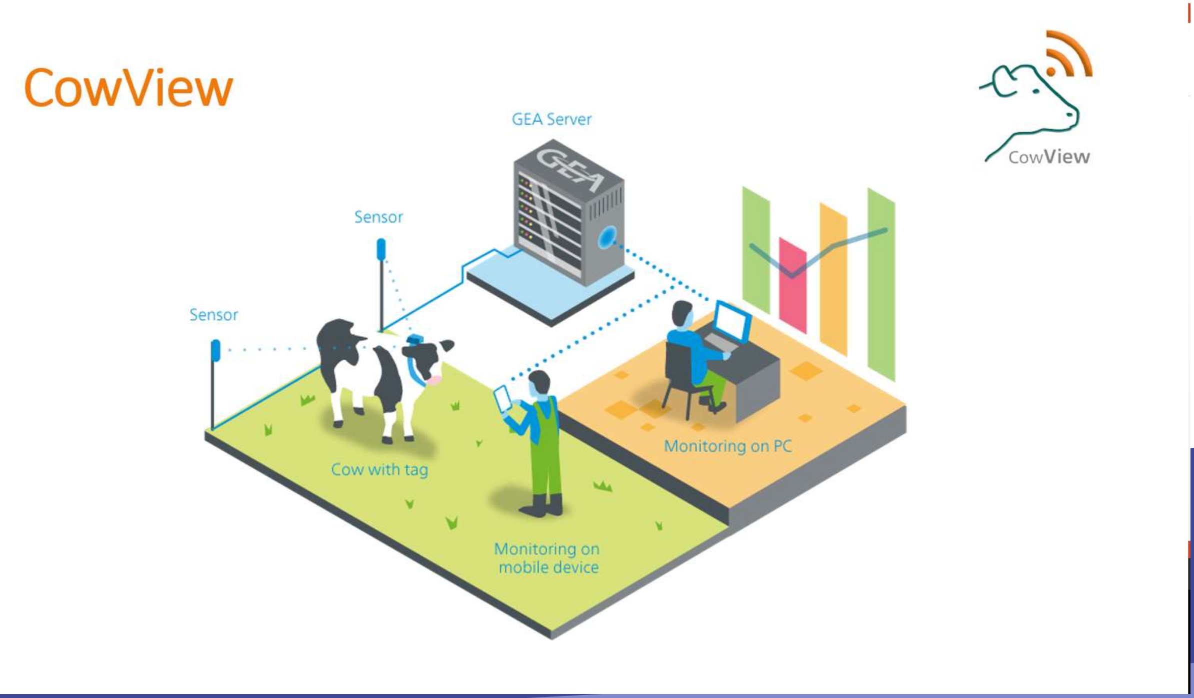
https://www.lely.com

Numerous changes to how the whole farm system is managed – cleaning and feed pushing

https://www.lely.com

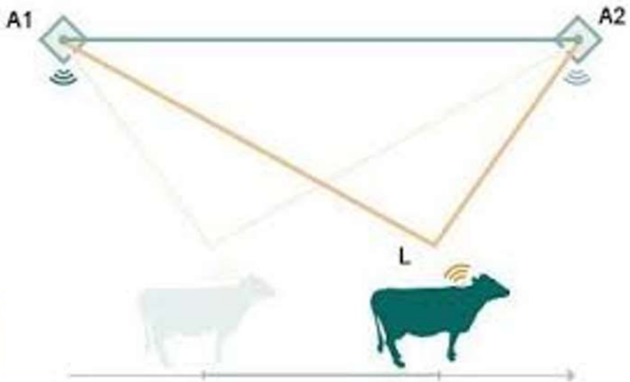
Behaviour cows – CowView real-time localisation of each animal

Sensor in the cow's identification collar - receiver in the barn, which transmits information to a computer, smartphone or tablet, in the form of graphics that are easy and quick to interpret.



Sensor

CowView

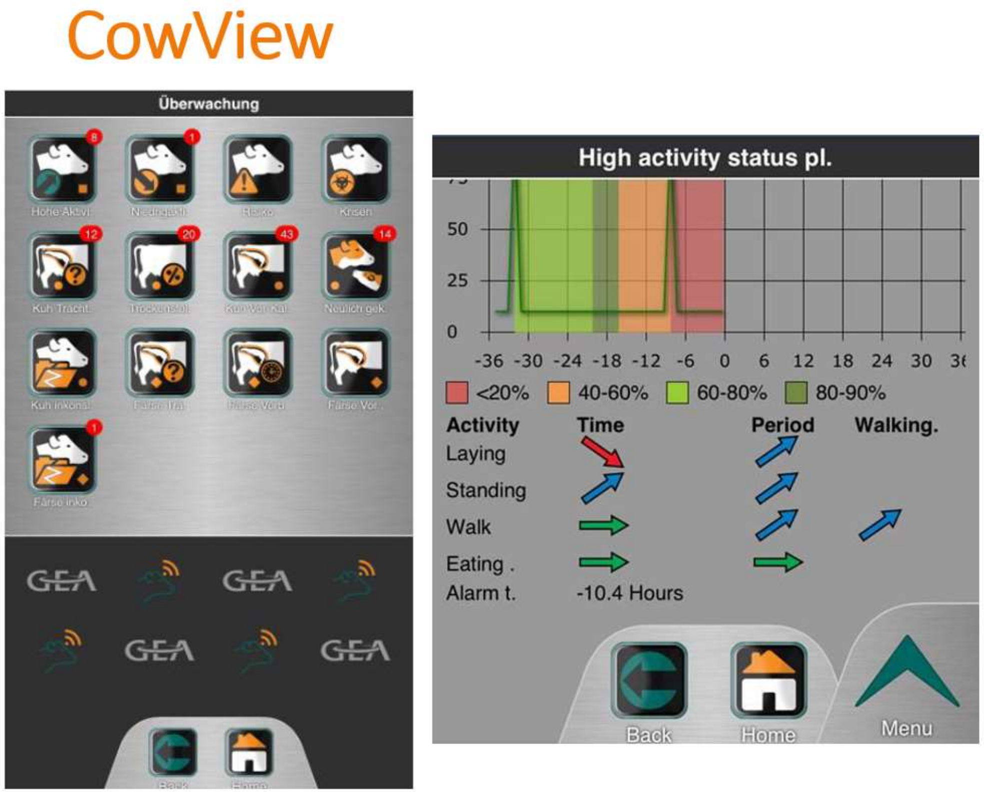


Information that is easy and quick to interpret

CowView

CowView

Information that is easy and quick to interpret



Information that is easy and quick to interpret

8:30 a.m.
The farmer begins his rounds in the stall.

8:31 a.m.
Warning via his smart-phone: Cow Lisa (355) shows reduced activity.

8:32 a.m.
The farmer takes a look at Lisa and her arched back tells him that she is lame.

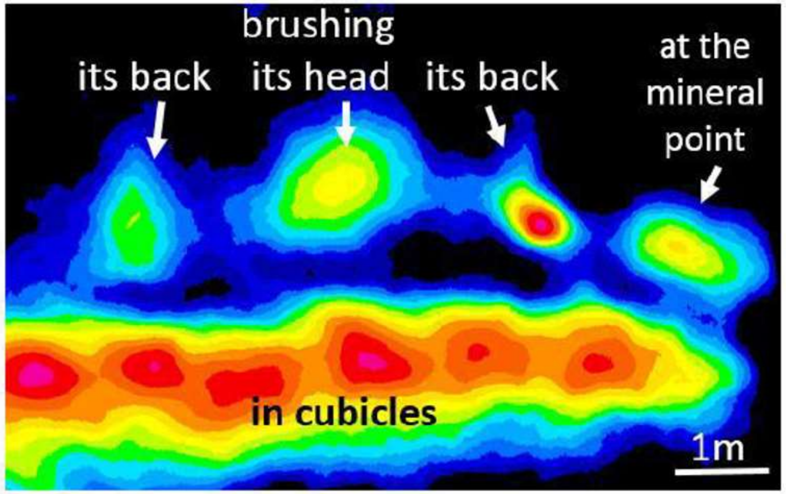
8:33 a.m.
Email sent to the hoof trimmer: Cow 355 is lame.

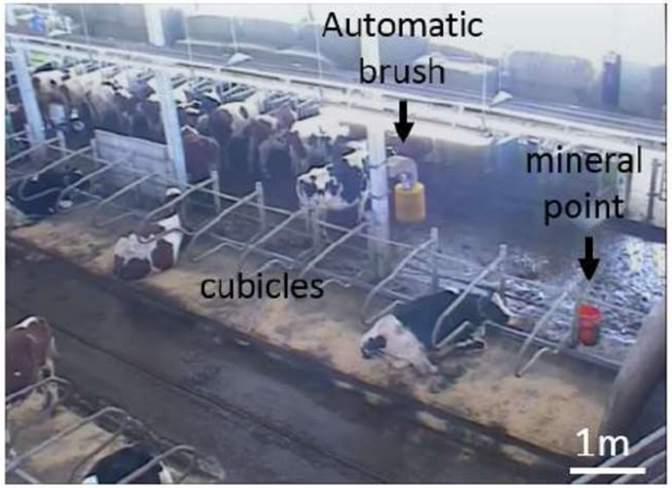
9:30 a.m.
GEA CowView shows the hoof trimmer where Lisa (355) is presently located; he treats and bandages the hoof. Wound control in 7 days.

9:30 a.m.
7 days later: GEA CowView shows the hoof trimmer where Lisa (355) is presently located; the hoof is treated once again.

Information that is easy and quick to interpret

CowView – Estudos





A.D. 1308
unipg
UNIVERSITÀ DEGLI STUDI
DI PERUGIA

Figura 1 e 2 – Coleira e respetivo dispositivo com sensor incorporado.

J. Dairy Sci. 103
https://doi.org/10.3168/jds.2019-17214

Symposium review: Future of housing for dairy cattle*

P. J. Galama,[1]† W. Ouweltjes,[1] M. I. Endres,[2] J. R. Sprecher,[3] L. Leso,[4] A. Kuipers,[1] and M. Klopčič[5]
[1]Wageningen Livestock Research, PO Box 338, 6700 AH, Wageningen, the Netherlands
[2]Department of Animal Science, University of Minnesota, 1364 Eckles Avenue, St. Paul 55108
[3]Sprecher Architects, Halamed Hey str. 10, Tel Aviv 6927710, Israel
[4]Department of Agricultural, Food and Forestry Systems, University of Florence, Via San Bonaventura, 13, IT-50145 Firenze, Italy
[5]Department of Animal Science, Biotechnical Faculty, University of Ljubljana, Groblje 3, Domžale, Slovenia

Figure 5. Use of composted bedding in freewalk housing for horticulture during the grazing period (Veld en Beek, Doorwerth farm, Heelsum, the Netherlands).

A.D. 1308 unipg UNIVERSITÀ DEGLI STUDI DI PERUGIA

Figure 2. Cow garden with artificial floor separating urine and manure, and small trees for shade and a natural look (Kraanswijk farm, Groenlo, the Netherlands).


...in consultation with companies
for better floor and manure robot...


Compost


Straw

https://www.youtube.com/watch?v=GOCy8nJ4XhY&t=135s

A.D. 1308
unipg
UNIVERSITÀ DEGLI STUDI
DI PERUGIA

UNIVERSITÀ DEGLI STUDI DI PERUGIA

Body condition is essential for production, reproduction, health and welfare of animals

J. Dairy Sci. 89:1–14

Invited Review: Methods to Determine Body Fat Reserves in the Dairy Cow with Special Regard to Ultrasonographic Measurement of Backfat Thickness

U. J. Schröder[1] and R. Staufenbiel
Klinik für Klauentiere, Freie Universität Berlin, D-14163 Berlin, Germany

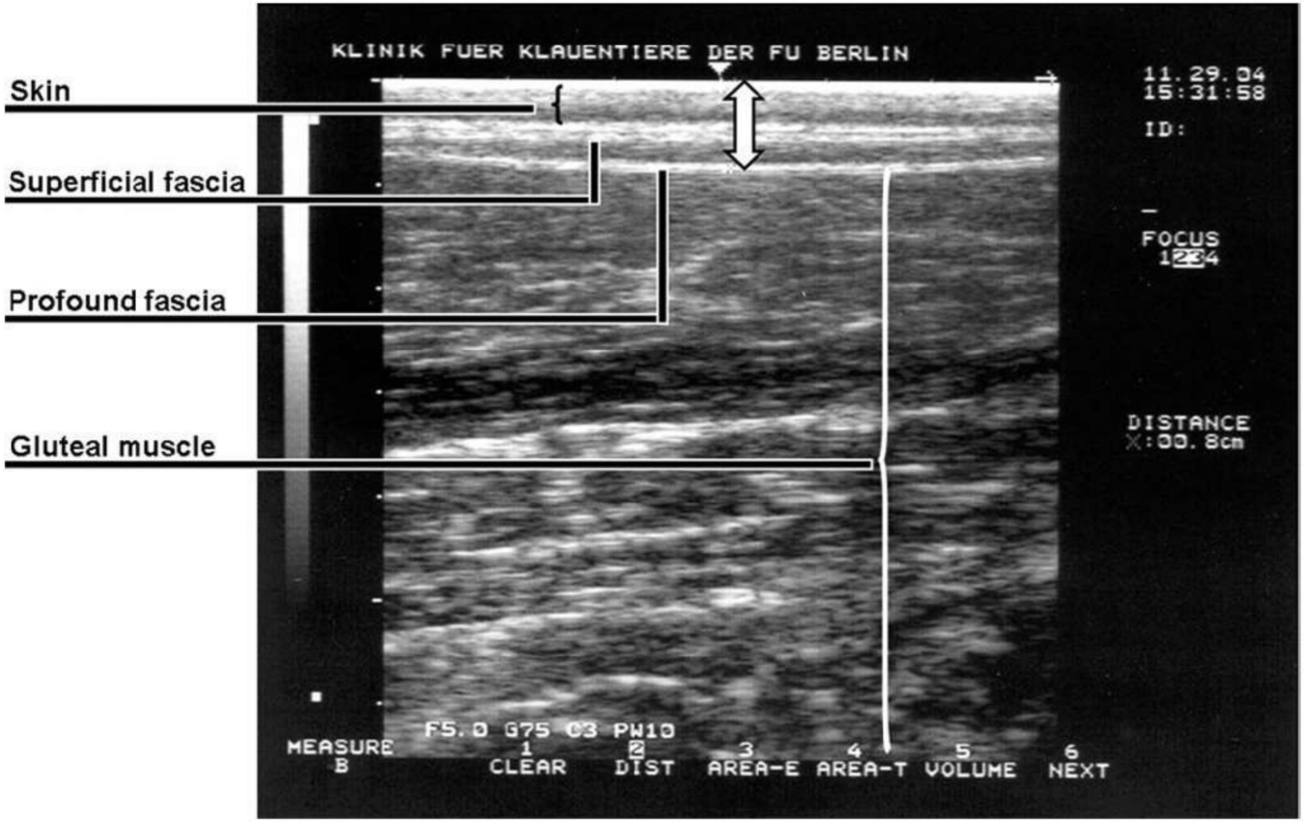
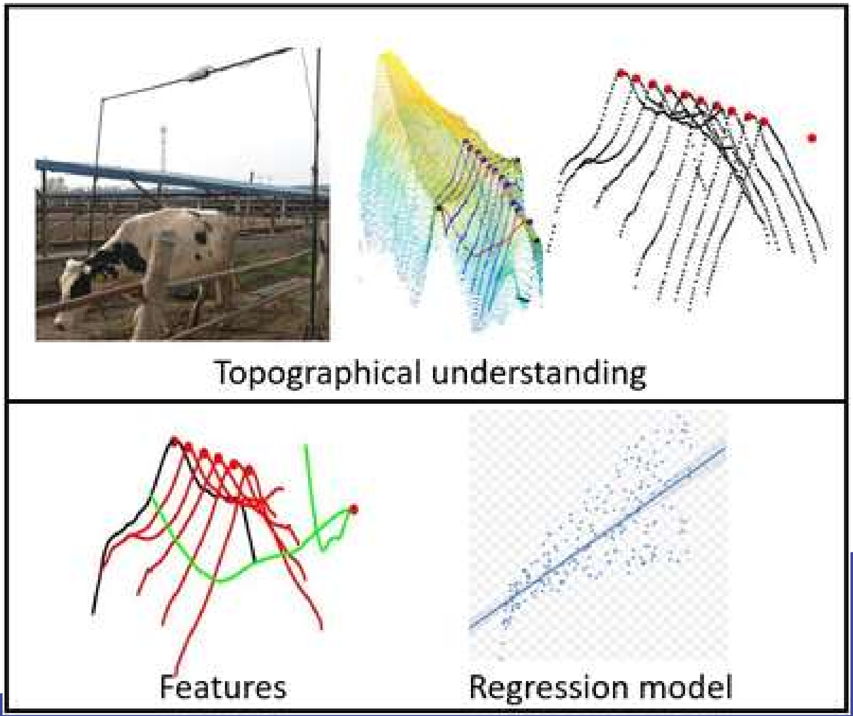


Figure 1. Ultrasound image illustrating backfat thickness (BFT) in a cow in poor condition (8 mm of BFT).

Estimation of body condition score by modeling cow body 3D shape using Kinect camera



https://www.biw.kuleuven.be/biosyst/a2h/m3-biores/home

Computers and Electronics in Agriculture 99 (2013) 35–40

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

ELSEVIER

Automatic assessment of dairy cattle body condition score using thermal imaging

I. Halachmi [a,*], M. Klopčič [b], P. Polak [c], D.J. Roberts [d], J.M. Bewley [e]

Thermal imaging

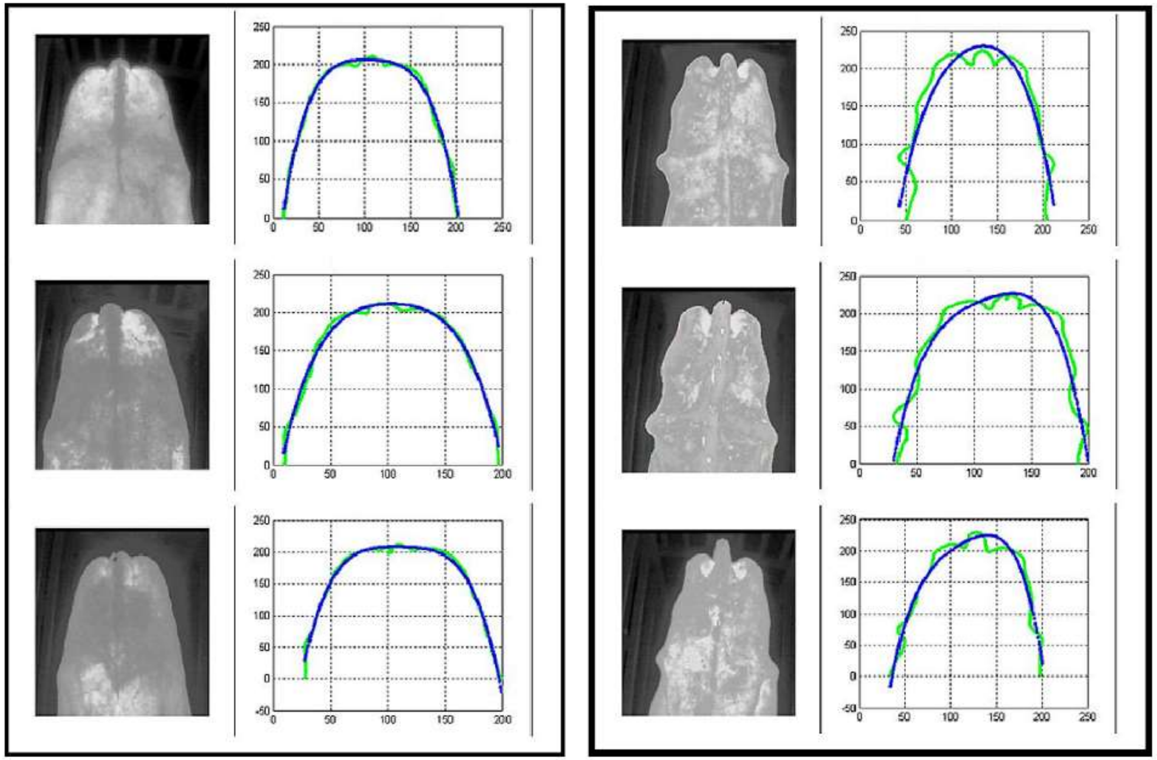
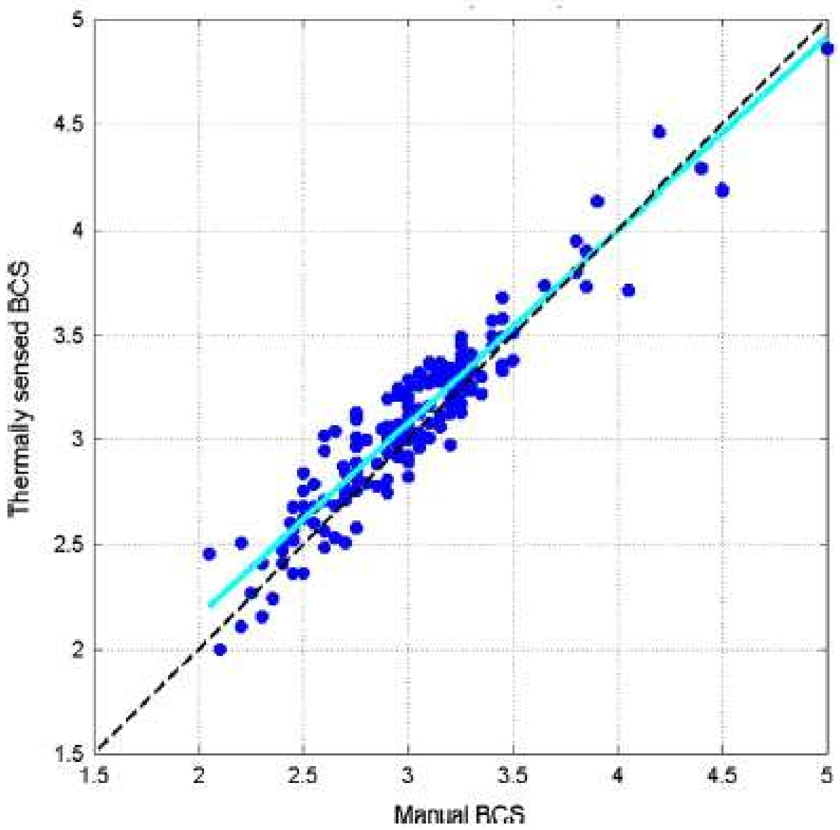


Fig. 2. Model inputs (left-side pictures) and their associated model outputs (right-side curves; the automatic extracted cow contour vs. automatic extracted fitted parabola). Thermal images taken from overhead: Left side: three fatter cows. Right side: three thinner cows.

Halachmi et al. (2013)

Thermal imaging



Halachmi et al. (2013)

UNIVERSITÀ DEGLI STUDI DI PERUGIA

J. Dairy Sci. 91:3439–3453
doi:10.3168/jds.2007-0836

Potential for Estimation of Body Condition Scores in Dairy Cattle from Digital Images

J. M. Bewley,*[1] A. M. Peacock,† O. Lewis,† R. E. Boyce,† D. J. Roberts,‡ M. P. Coffey,§ S. J. Kenyon,# and M. M. Schutz*
*Department of Animal Science, Purdue University, West Lafayette, IN 47907
†IceRobotics Ltd., Roslin BioCentre, Roslin, Midlothian, EH25 9TT United Kingdom
‡Sustainable Livestock Systems Group, Scottish Agricultural College, Crichton Royal Farm, Midpark House, Dumfries, DG1 4SZ United Kingdom
§Sustainable Livestock Systems Group, Scottish Agricultural College, Bush Estate, Penicuik, Midlothian, EH26 0PH United Kingdom
#Department of Veterinary Clinical Sciences, Purdue University, West Lafayette, IN 47907

A.D. 1308 unipg UNIVERSITÀ DEGLI STUDI DI PERUGIA

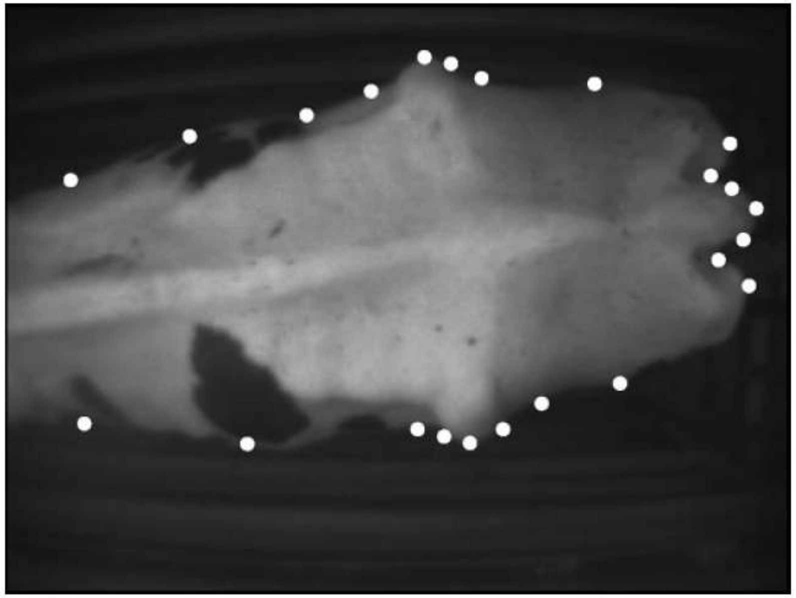


Figure 1. Twenty-three key anatomical points identified (where possible) for each image.

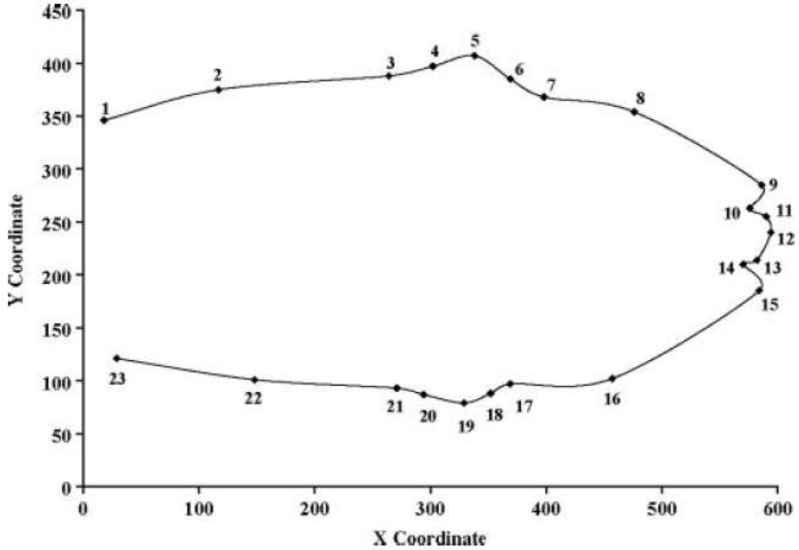
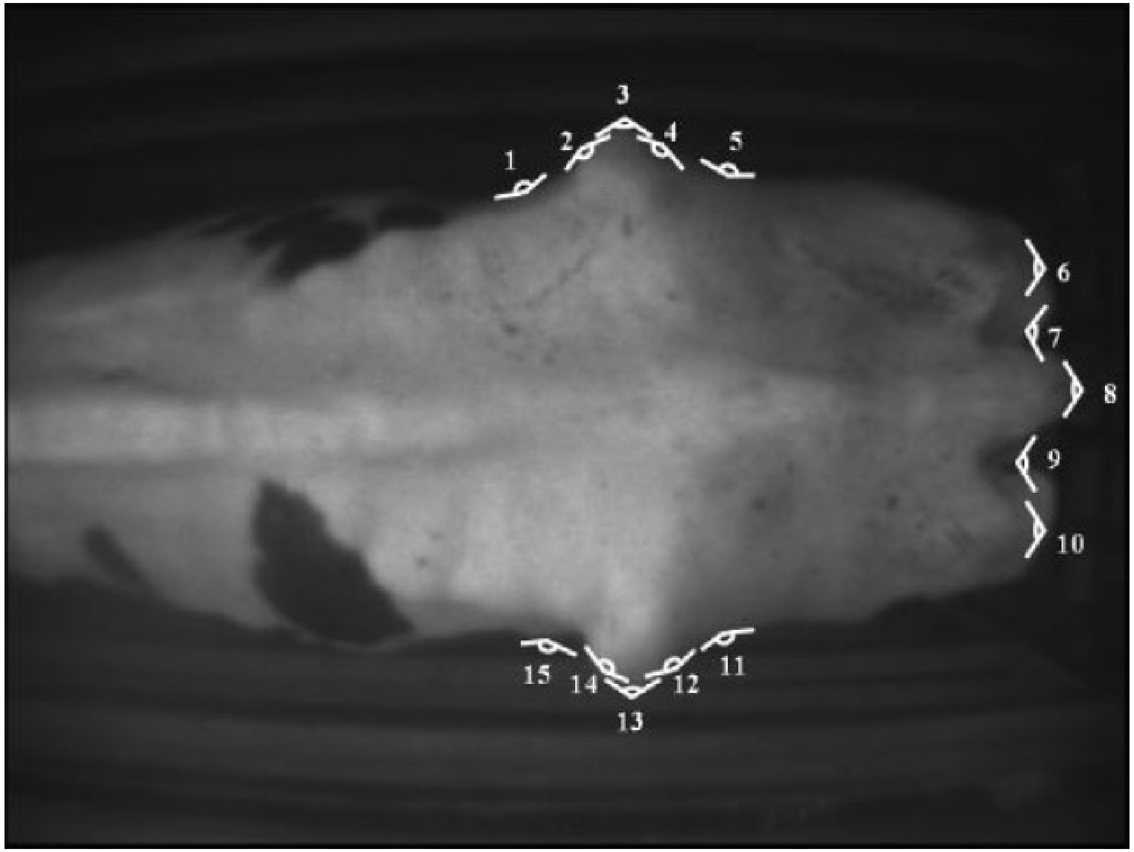


Figure 2. Sample cow outline using 23 key anatomical points: 1) left forerib, 2) left short rib start, 3) left hook start, 4) left hook anterior midpoint, 5) left hook, 6) left hook posterior midpoint, 7) left hook end, 8) left thurl, 9) left pin, 10) left tailhead nadir, 11) left tail-head junction, 12) tail, 13) right tailhead junction, 14) right tailhead


1
2
3
4
5
6
7
8
9
10
11
12
13
14
15

When the full data set testing only the angles around the hooks was used, 100% of predicted BCS were within 0.50 points of actual USBCS and 92.79% were within 0.25 points;

and 99.87% of predicted BCS were within 0.50 points of actual UKBCS and 89.95% were within 0.25 points.

J. Dairy Sci. 91:4444–4451
doi:10.3168/jds.2007-0785

Cow Body Shape and Automation of Condition Scoring

I. Halachmi,*[1] P. Polak,† D. J. Roberts,‡ and M. Klopcic§
*Institute of Agricultural Engineering, Agricultural Research Organization, Volcani Center, Bet Dagan 50250, Israel
†Research Institute for Animal Production, Slovak Agricultural Research Center, 949 92 Nitra, Slovakia
‡Scottish Agricultural College Dairy Research Centre, Crichton Royal Farm, Dumfries DG1 4SZ, UK
§Department of Animal Science, Biotechnical Faculty, University of Ljubljana, 1230 Domzale, Slovenia

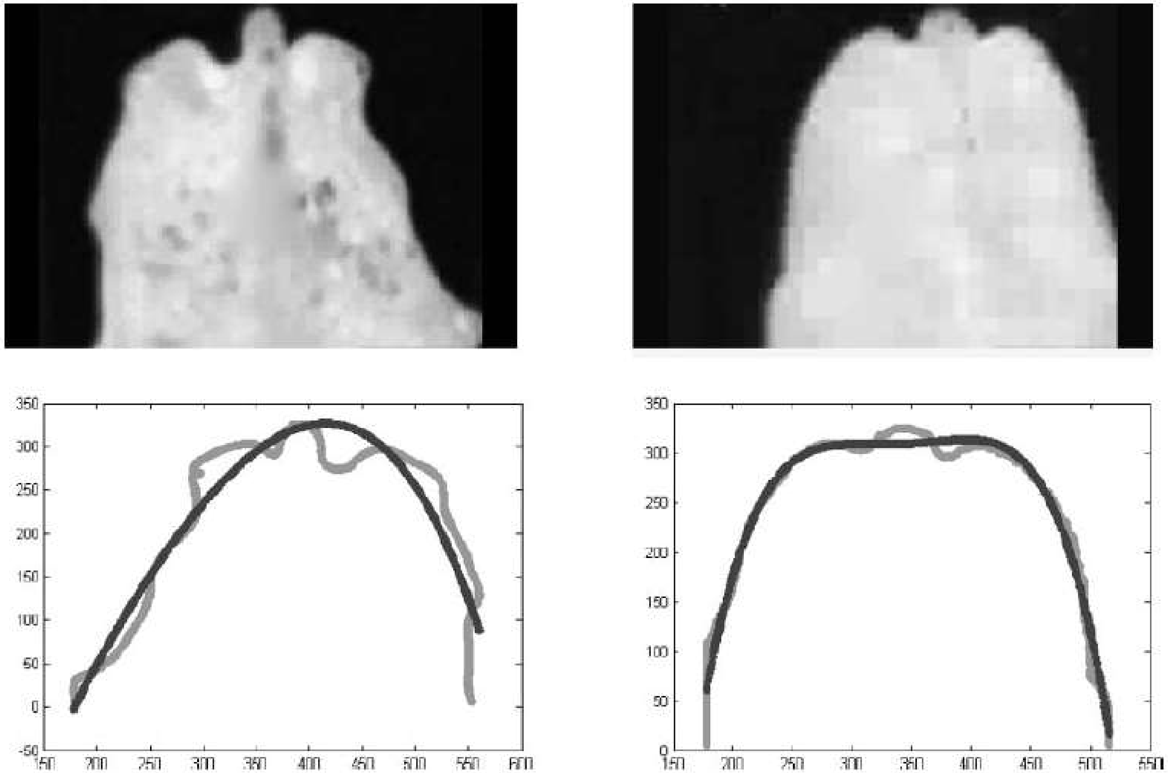


Figure 2. A thin cow (left, cow number 1358) and a fat cow (right, cow number 1640). Upper pictures are the model inputs: thermal images taken from overhead. Lower pictures are the model outputs: cow contour vs. fitted parabola. The fat cow (1640): manual BCS = 3.0, ultrasound-measured fat plus muscle thickness = 74 mm (3.52 in BCS units). Model thermal BCS = 3.50. The thin cow (1358): manual BCS = 1.25, ultrasound-measured fat plus muscle thickness = 40 mm (1.44 in BCS units). Model thermal BCS = 1.3.

3D images

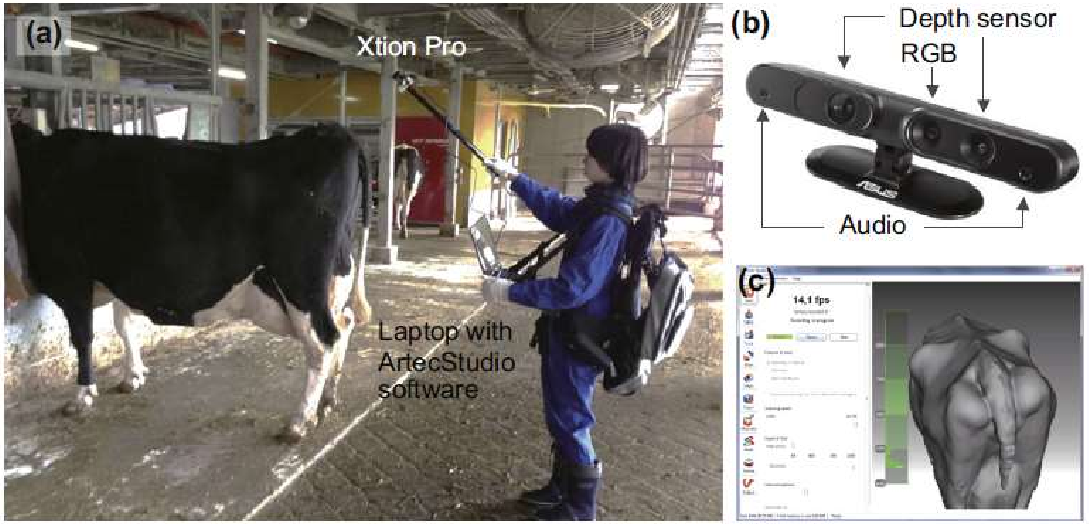
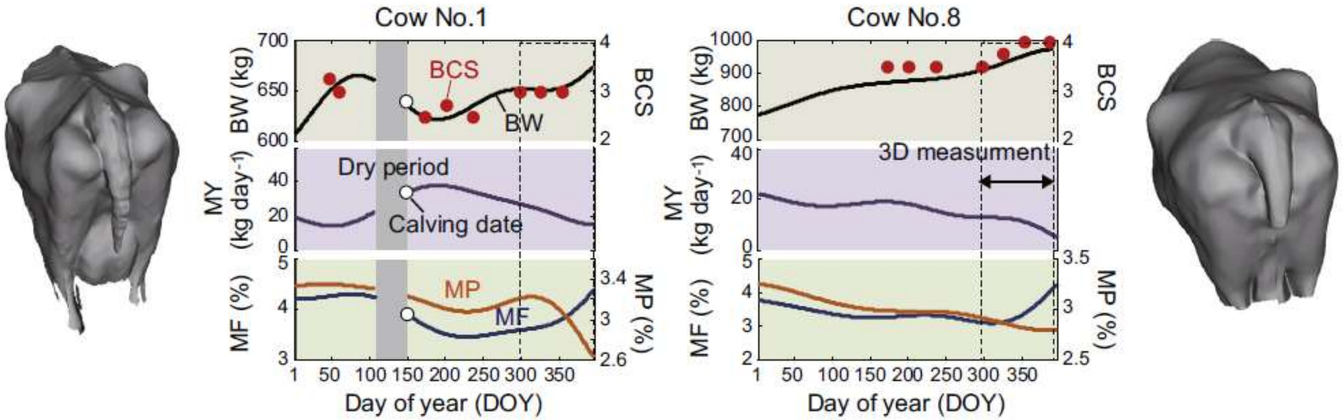


Fig. 2. Back posture measurement of dairy cow with 3D camera. (a) Measurement was conducted inside cowshed of the Hiroshima University's farm at morning feeding (9:30–10:30) by an observer carrying the 3D camera and laptop computer. (b) Sensors and their position on the ASUS Xtion Pro (ASUSTeK Computer Inc.). (c) Laptop screen displaying a 3D image of cow on the Artec Studio 9.2 software.

Kuzuhara et al. (2015)

Y. Kuzuhara et al./Computers and Electronics in Agriculture 111 (2015) 186–193



A.D. 1308
unipg
UNIVERSITÀ DEGLI STUDI DI PERUGIA

Automatic Determination of Body Condition Score of Dairy Cows from 3D Images

Processing and pattern recognition
in images from a time-of-flight camera

Figures 3.2: The setup when collecting the images with me and a cow in the research-barn.

Figure 5. The automatic scale, DeLaval Automatic Weight System (AWS 100).

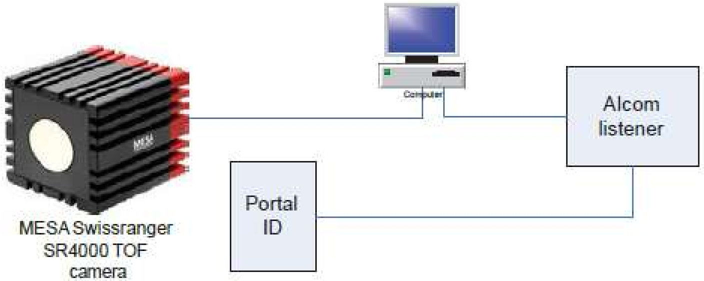


Figure 6. MESA time-of-flight (TOF) DeLaval camera for 3D image collection, an Alcom listener; the connecting units and a computer storing collected data.

A.D. 1308 unipg UNIVERSITÀ DEGLI STUDI DI PERUGIA

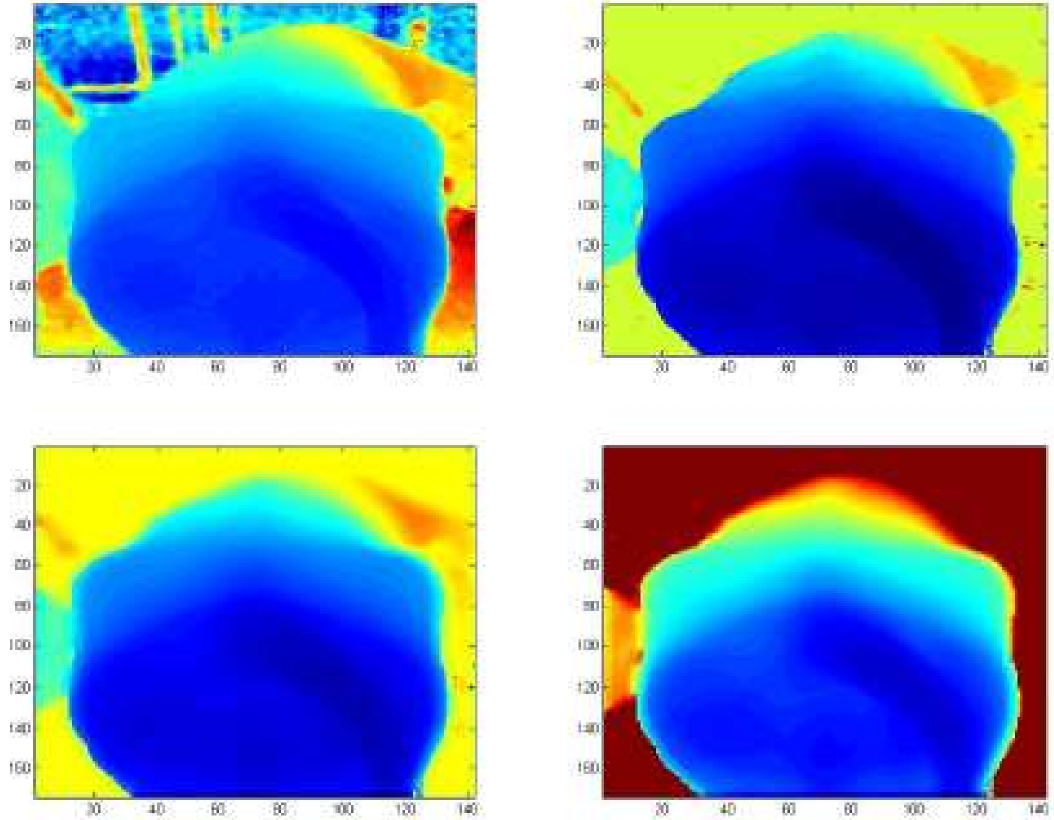


Figure 4.3: From above, left: Range images of original data, intensity-filtered data, average filtered data, and finally; range-filtered data.

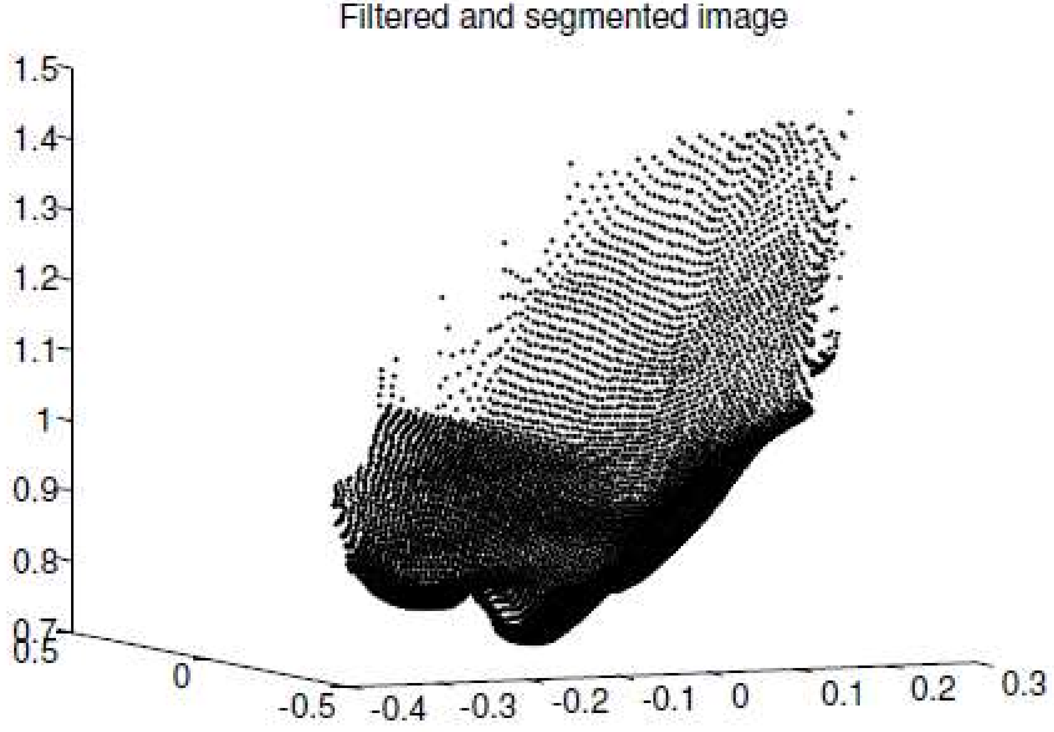


Figure 4.4: Segmentation of data isolating the surface of the cow

A.D. 1308 unipg UNIVERSITÀ DEGLI STUDI DI PERUGIA

Computers and Electronics in Agriculture 165 (2019) 104958

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

Cattle segmentation and contour extraction based on Mask R-CNN for precision livestock farming

Yongliang Qiao*, Matthew Truman, Salah Sukkarieh

Australian Centre for Field Robotics (ACFR), Faculty of Engineering, The University of Sydney, NSW 2006, Australia

A.D. 1308

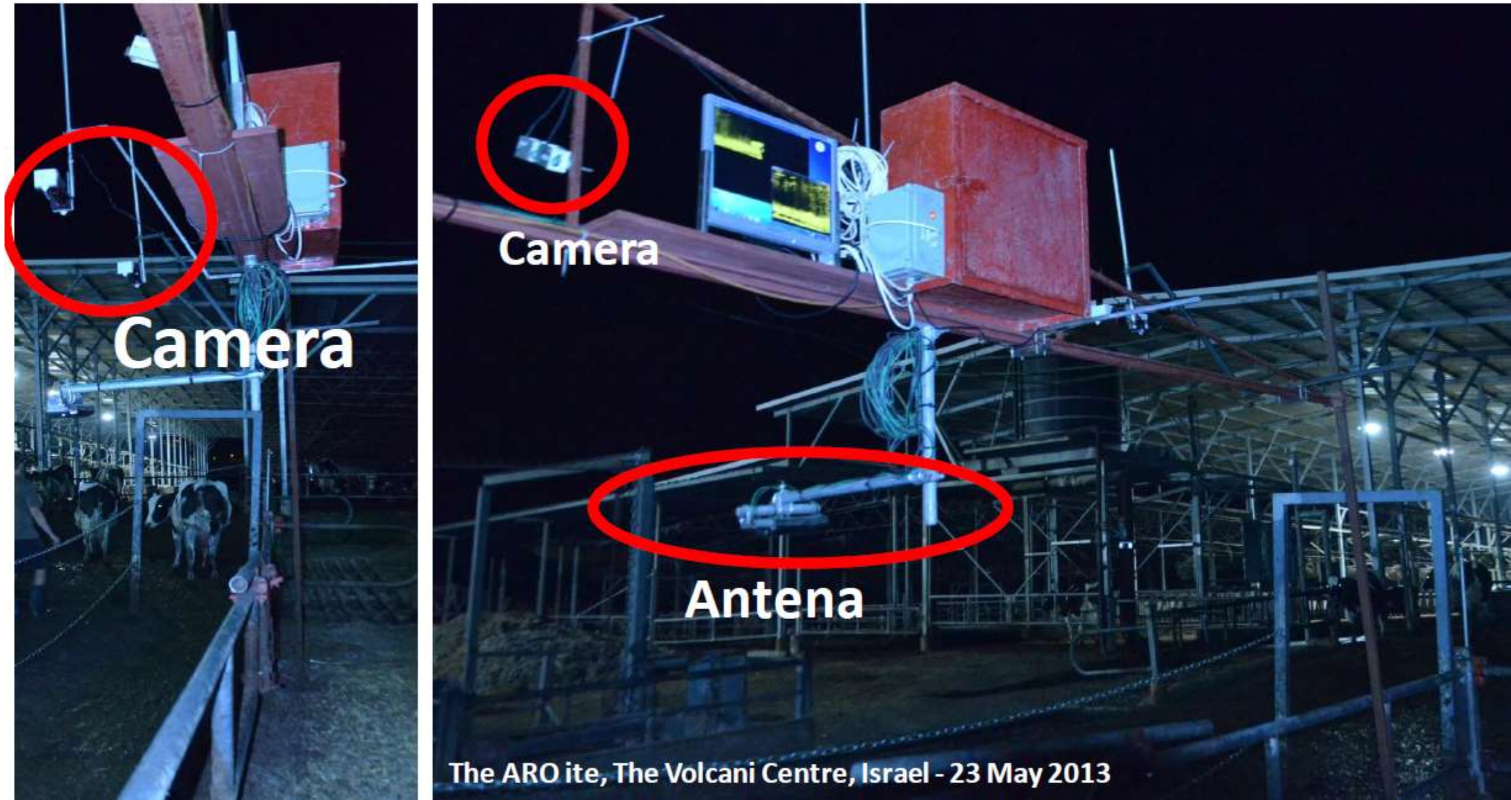
UNIVERSITÀ DEGLI STUDI DI PERUGIA

(a) Enhaced images

(b) Mask R-CNN segmentation

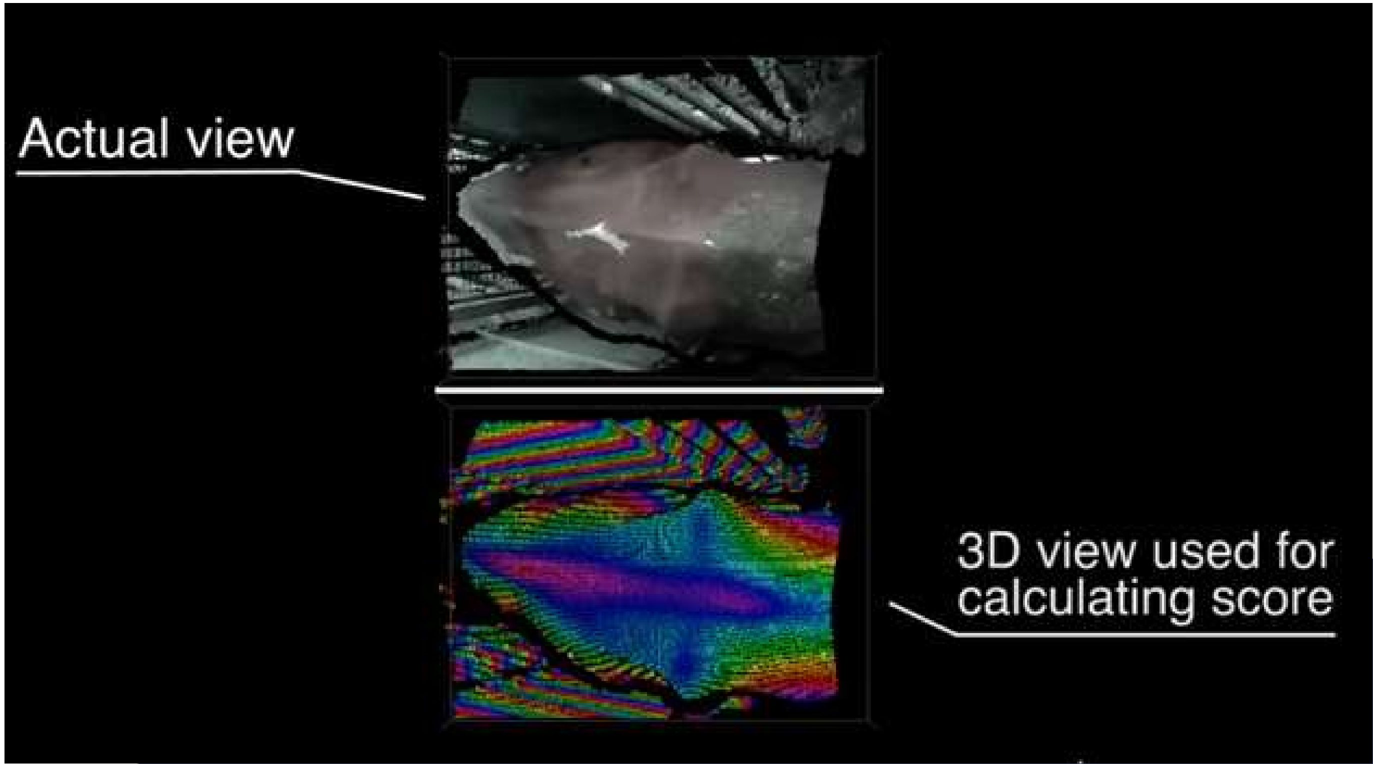
Fig. 7. The proposed Mask R-CNN based multi-cattle segmentation results. Examples of the enhanced images are displayed in the top row and their corresponding Mask R-CNN segmentation results are illustrated in the bottom row. Each color area indicates a segmented cattle instance. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

3D image



Halachmi et al. (2015)

3D image



http://www.delavalcorporate.com/

3D image

http://www.delavalcorporate.com/

Goats 3D image

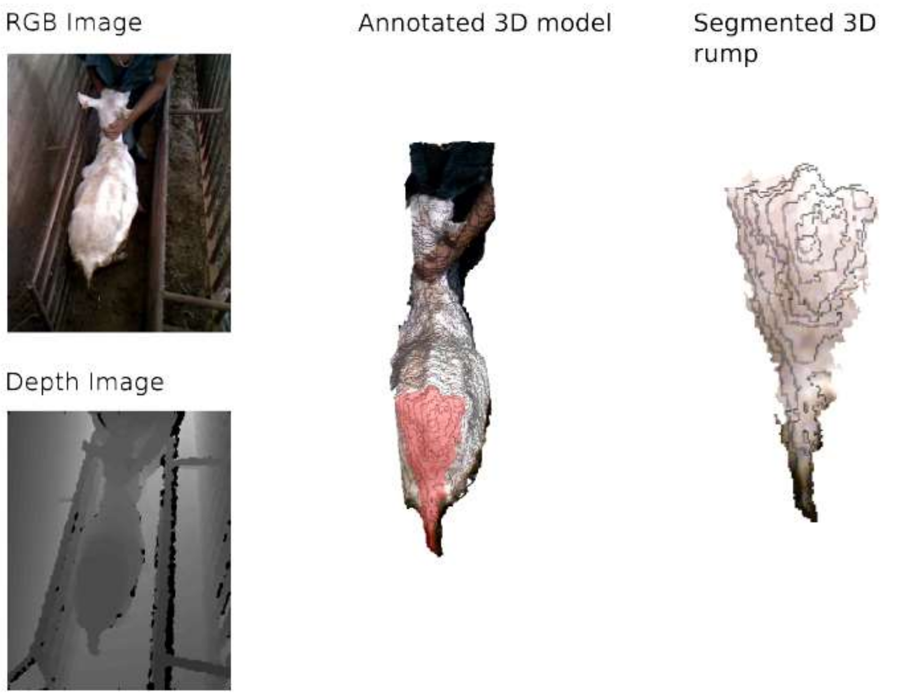


Fig. 2. Acquiring rumps' 3D surfaces.

Brandão et al. (2015)

UNIVERSITÀ DEGLI STUDI DI PERUGIA

Goats 3D image

L'imagerie 3D : une autre méthode d'évaluation de l'état corporel chez la chèvre Alpine.

3D imaging: another method of assessing body condition in the Alpine goat.

Contacts:
christophe.huau@inrae.fr

HUAU C. (1), POMMARET A. (2), AUGERAT D. (3), MARECHAL P. (3), DELATTRE L. (4), RUPP R. (1)

(1) INRAE, INPT-ENVT, INPT-ENSAT, GenPhySE, 31326 Castanet-Tolosan, France
(2) Station expérimentale du Pradel, 07170 Mirabel, France
(3) INRAE UE332, Domaine de Bourges-La Sapinière, F-18390 Osmoy
(4) 3DOUEST, 5 Rue de Broglie, 22300 Lannion, France

Huau et al. (2020)

A.D. 1308 unipg
UNIVERSITÀ DEGLI STUDI DI PERUGIA

MATÉRIEL

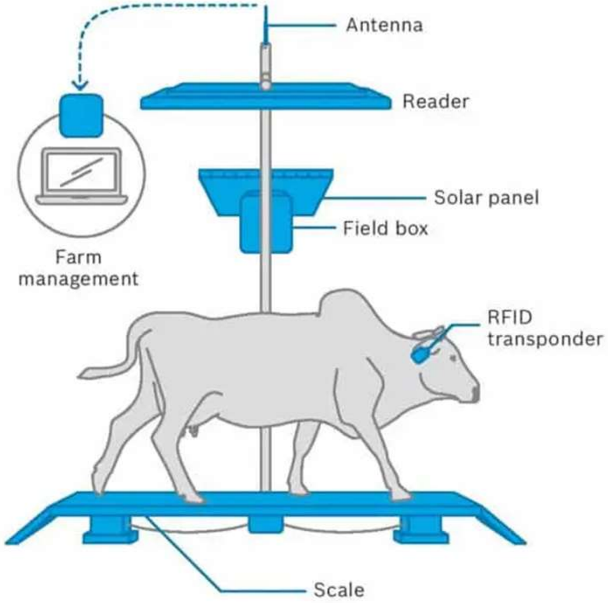
45 CHÈVRES

Image en 3 dimensions sur zone lombaire et bassin:
3D type Asus Xtion / Primesense Carmine fixé sur tablette
Logiciel développé par 3D Ouest

Cow3DPointage

Obtention de 2 images: 1 au format .png et 1 au format .obj sur les 2 sites anatomiques

Weighing platform



https://blog.bosch-si.com/agriculture/a-closer-look-at-precision-livestock-farming/

Information on the daily growth rate of animals enables the stockman to monitor their performance and health and to predict and control their market weight

Kinect Live weight pigs

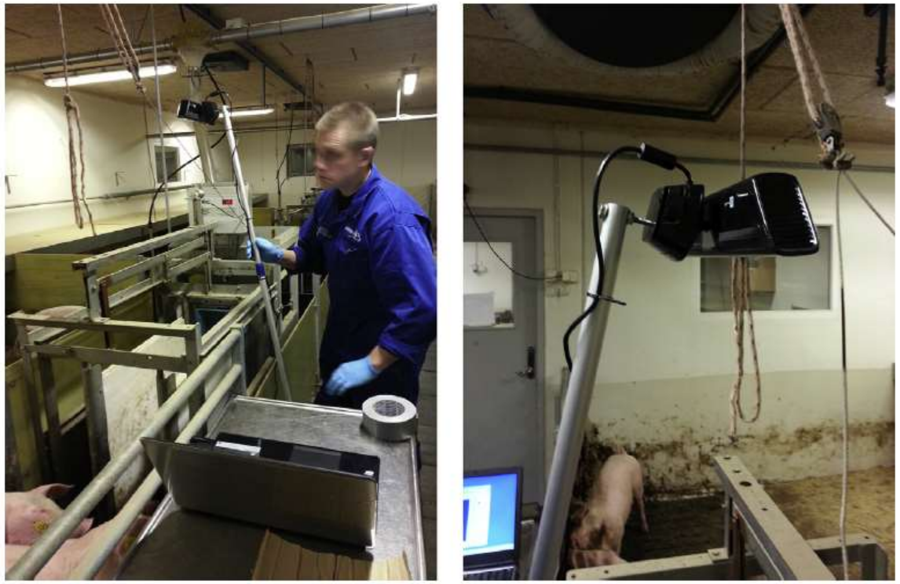


Fig. 1. Kinect prototype.

Kongsro (2014)

Kinect Live weight pigs

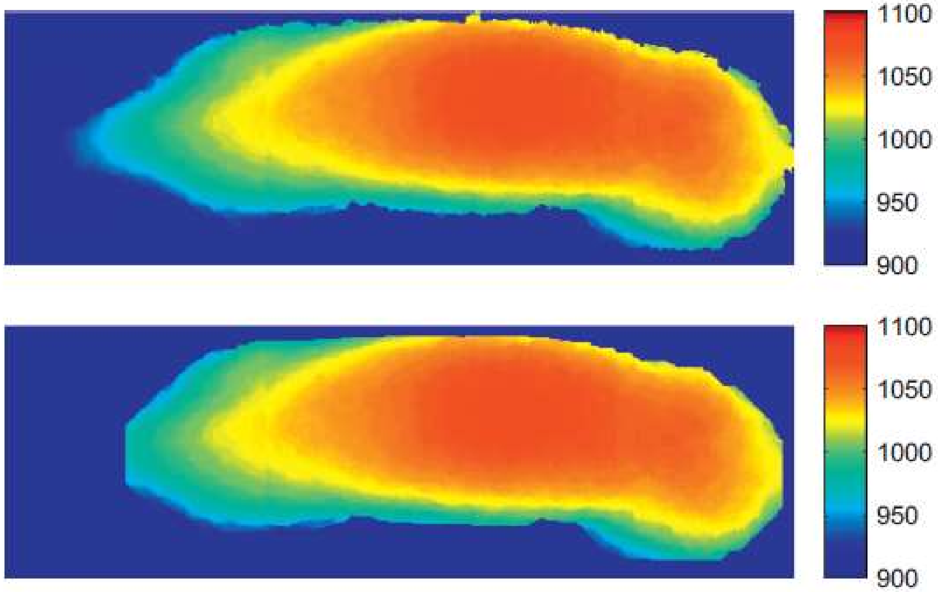


Fig. 2. Depth image and before (top) and after morphological filtering (bottom). Distance is in millimeters.

Kongsro (2014)

Kinect Live weight pigs

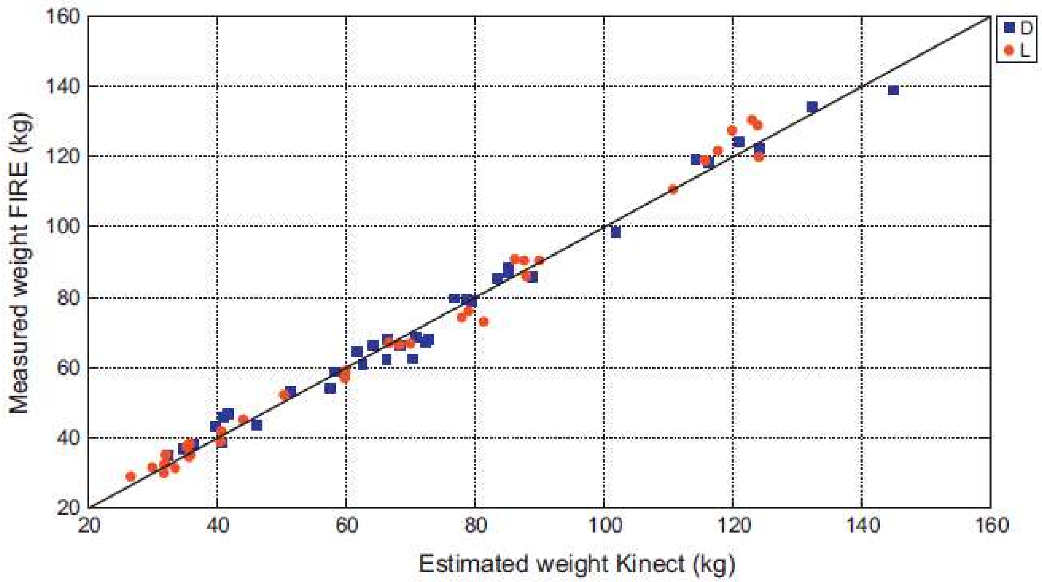


Fig. 5. Scatter plot; measured FIRE weight vs. estimated Kinect weight by breed.

Kongsro (2014)

A.D. 1308
unipg
UNIVERSITÀ DEGLI STUDI
DI PERUGIA

Computers and Electronics in Agriculture 107 (2014) 38–44

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

ELSEVIER

Automatic weight estimation of individual pigs using image analysis

CrossMark

Mohammadamin Kashiha [a,*], Claudia Bahr [a], Sanne Ott [b,c], Christel P.H. Moons [b], Theo A. Niewold [c], Frank O. Ödberg [b], Daniel Berckmans [a]

[a] *M3-BIORES – Measure, Model & Manage Bioresponses, Department of Biosystems, KU Leuven, Kasteelpark Arenberg 30, B-3001 Leuven, Belgium*
[b] *Department of Animal Nutrition, Genetics, Breeding and Ethology, Ghent University, Heidestraat 19, B-9820 Merelbeke, Belgium*
[c] *Division of Livestock-Nutrition-Quality, Department of Biosystems, KU Leuven, Kasteelpark Arenberg 30, B-3001 Leuven, Belgium*

Live weight pigs

Berckmans, 2017

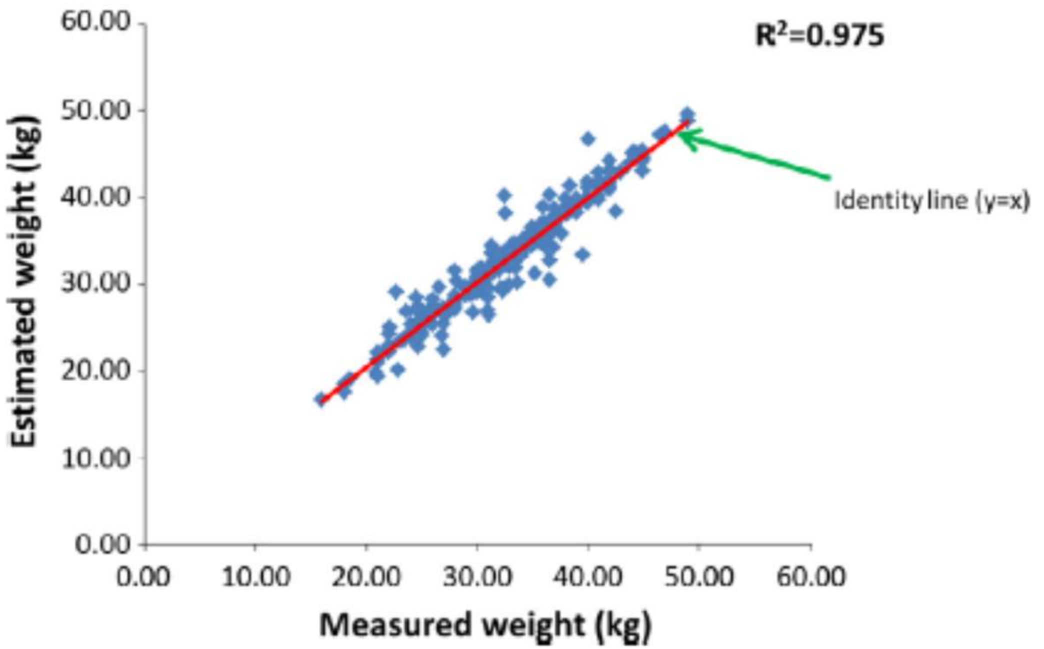


Fig. 7. Measured weights versus estimated weights over six measurement days of all four pens with ten pigs per pen (240 data points) in the validation experiment. Overall R^2 is 0.975 with standard error of 0.0182.

Computers and Electronics in Agriculture 123 (2016) 319–326

Contents lists available at ScienceDirect

ELSEVIER

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

Original papers

Weight prediction of broiler chickens using 3D computer vision

Anders Krogh Mortensen [1], Pavel Lisouski [1], Peter Ahrendt *

Aarhus University, Department of Engineering, Finlandsgade 22, 8200 Aarhus N, Denmark

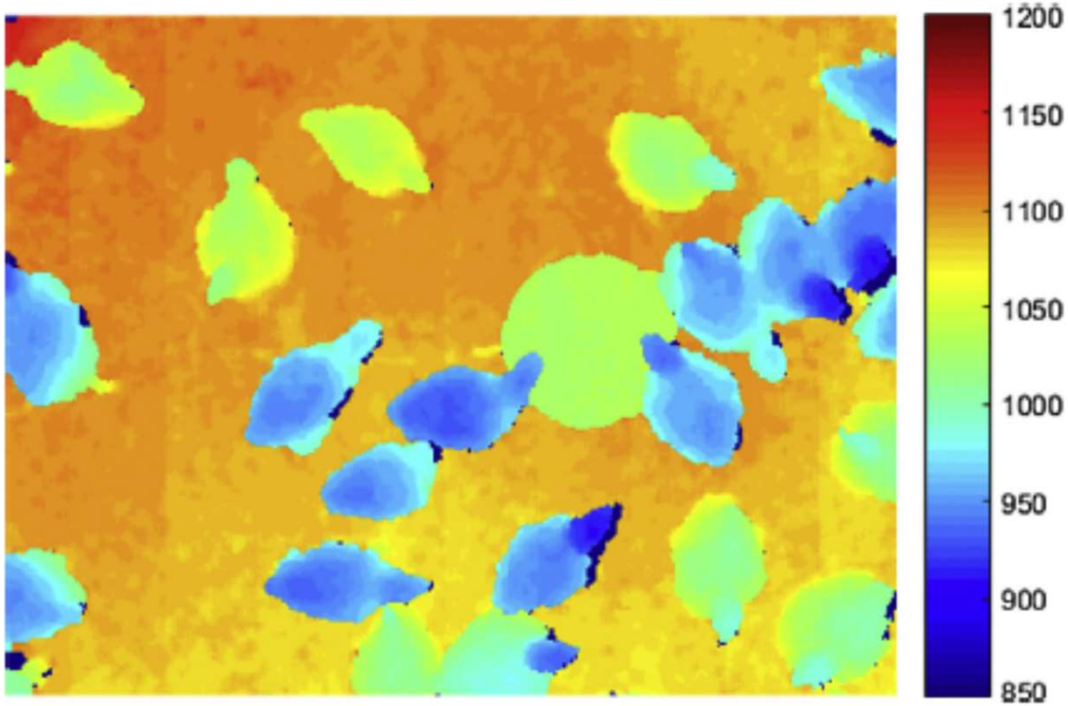


Fig. 1. Depth image taken with the Kinect camera. The different colors directly show the distance from the camera to a position in the image and can therefore be seen as a 3D representation. The scale bar shows the distance in milimeters from the Kinect camera to an object. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

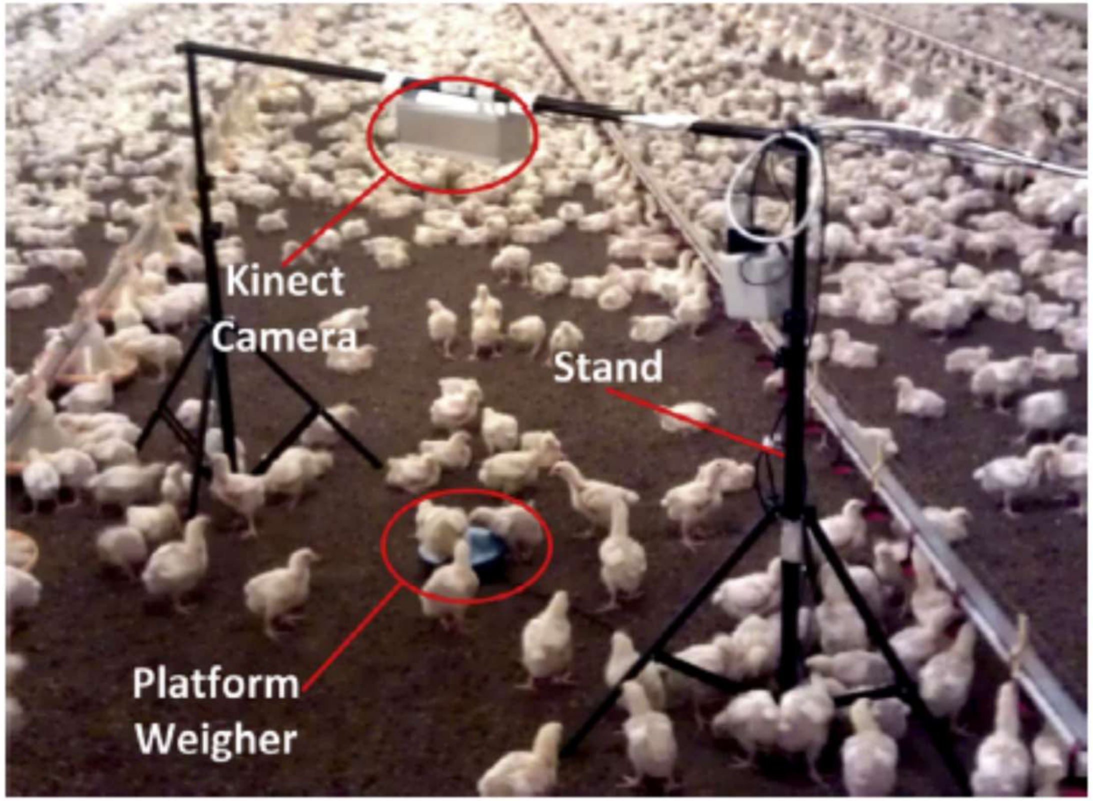


Fig. 3. Photo of the experimental arrangement. The photo was taken the same day the system was set up in the broiler stand – the 14th day of the rearing period. Note that at this photo, the broilers are still avoiding the camera stand where they would normally be standing as closely together as seen in the rest of the stable.

UNIVERSITÀ DEGLI STUDI DI PERUGIA

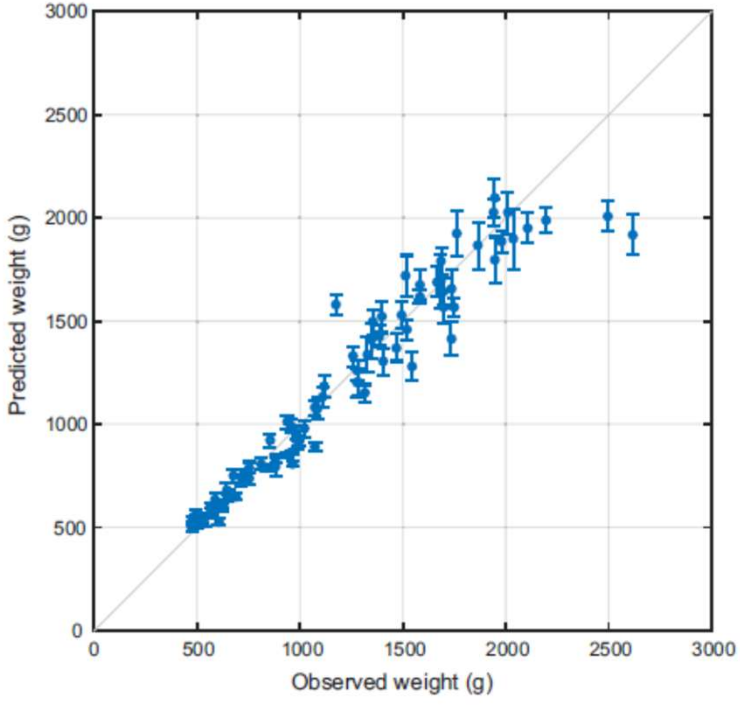
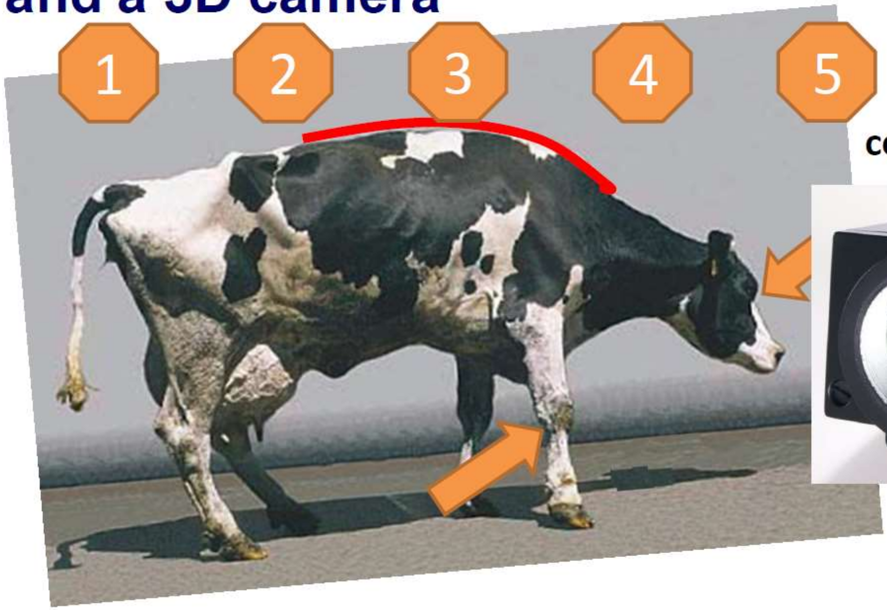


Fig. 9. Correlation plot for each broiler in the test set. The dot shows the average predicted broiler weight of a given broiler, and the error bars correspond to one standard deviation.

Lameness

Automatic lameness detection

Could use: Lying behavior , Rumination, Neck Activity, Body Weight, Milk components. etc , and a 3D camera



Halachmi et al (2013)

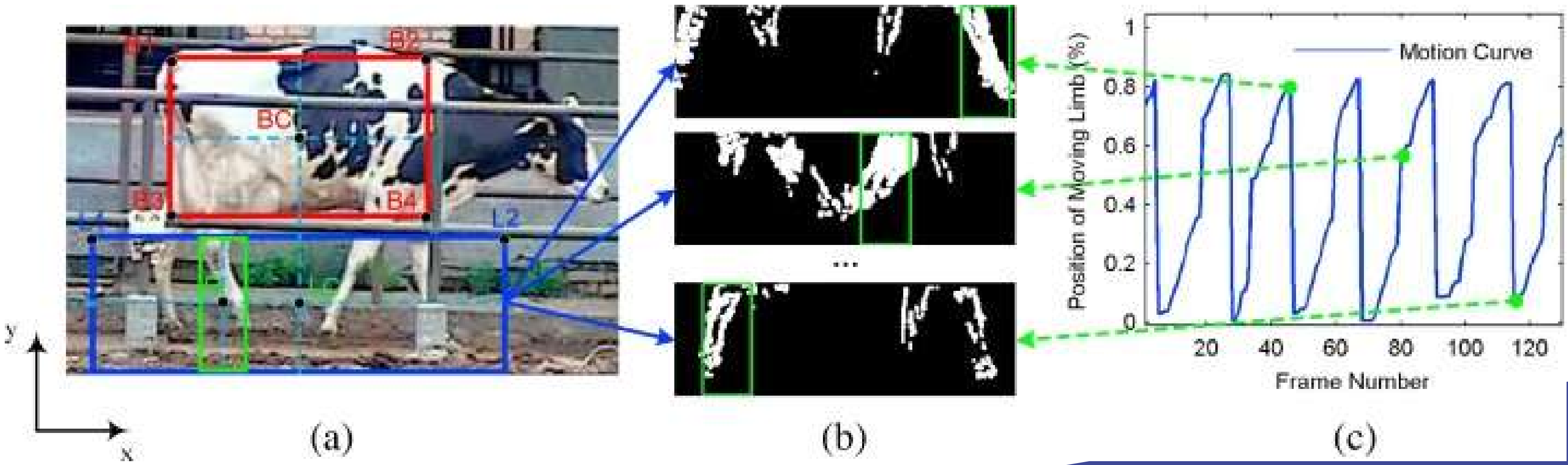
Overall system’s ability to **detect an early lameness onset with high accuracy** using **real-world, commercial-farm routine and unconstrained data** is the ultimate goal of a system

Two approaches

Motion-Image

Force sensors

Lameness



Zhao et al., 2018

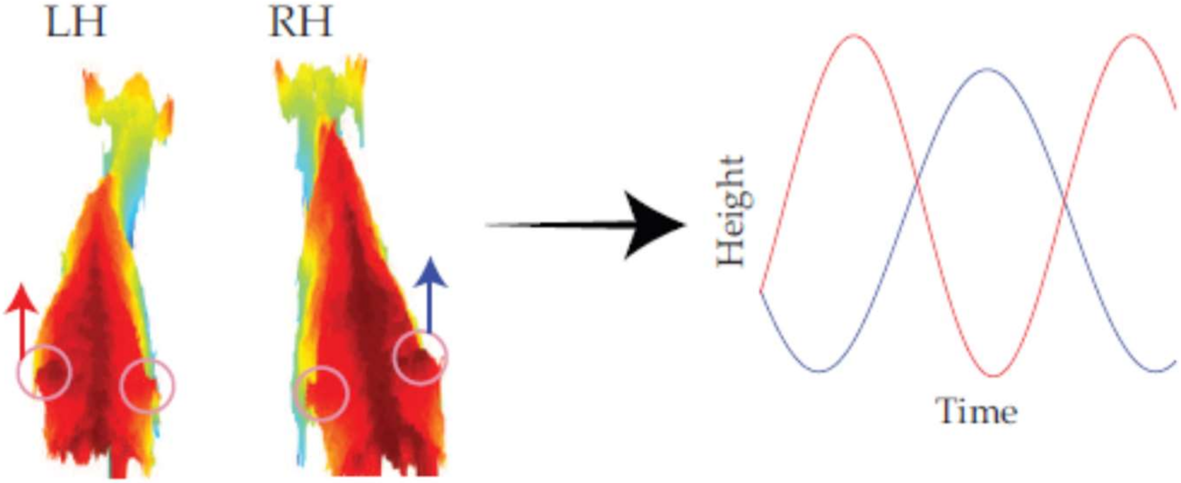
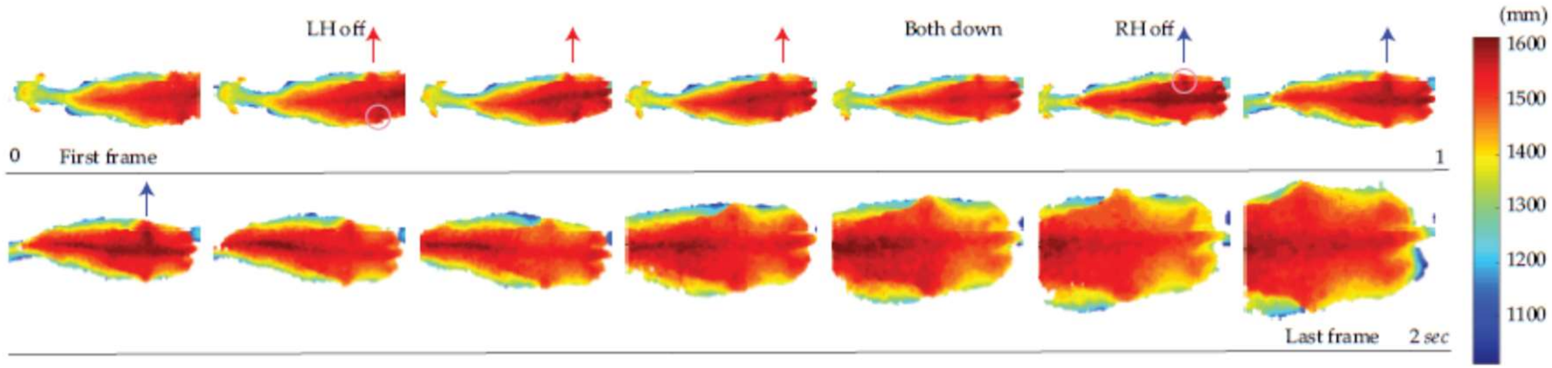


FIGURE 4.1: Visualisation of the gait asymmetry proxy. The darkened regions in both 3D representation images/frames reveal higher pixels indicating that leg is moving up in that frame. By tracking those regions (hook bones), a dynamic proxy is derived from the entire video to represent the locomotion in the form of height movements or 'vertical' movements (shown in the plot on the right).



LH off
Both down
RH off
0
First frame
1
Last frame
2 sec
(mm)
1600
1500
1400
1300
1200
1100

A.D. 1308
unipg
UNIVERSITÀ DEGLI STUDI DI PERUGIA

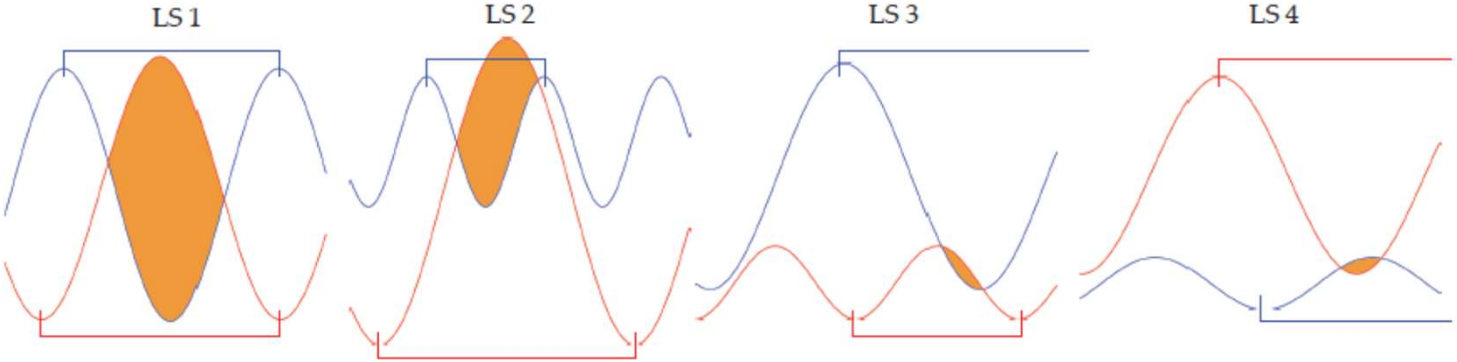


Figure 4.15: Summary of the gait asymmetry trends on LS 1, 2, 3 and 4 cows. Notice the clear difference in the length of a period T (indicated as a bracket) between right (blue) and left (red) signals. Lameness also affects the symmetry of the signals, peak vs peak amplitude/width and frequency difference. The identical 'reversed polarity' pattern decreases with lameness.

Fig. 1. Side view recording setup with dynamic background (top); Side view recording setup with static background (bottom).

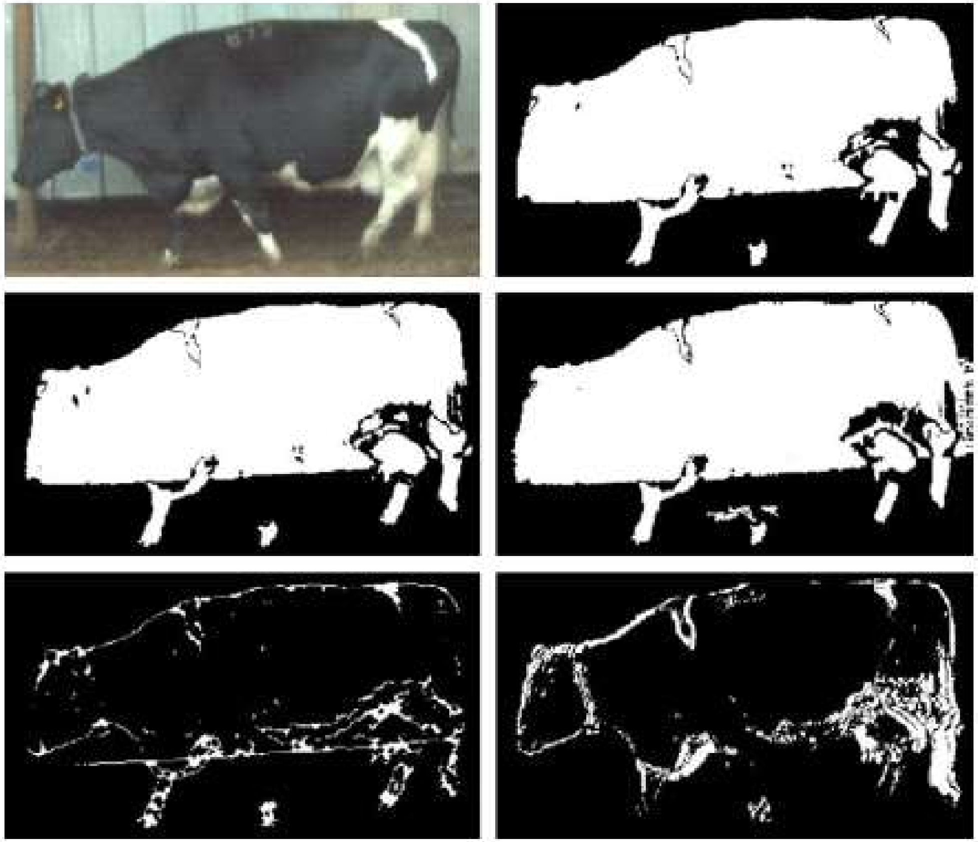


Fig. 2. Segmentation outputs of listed algorithms; Original cow frame (top-left); Algorithm 1 [FDBG] (top-right); Algorithm 2 [NLCC] (mid-left); Algorithm 3 [UNLCC] (mid-right); Algorithm 4 [cowEdge] (bottom-left); and algorithm 5 [CFDM] (bottom-right).

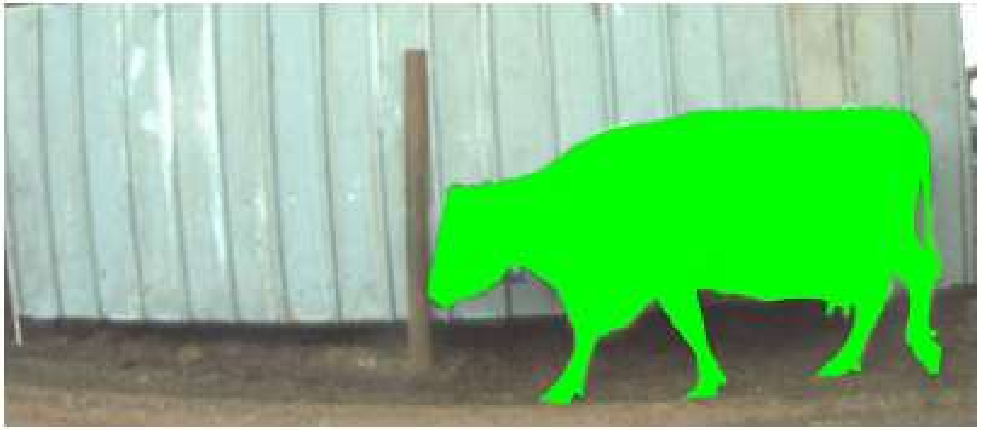


Fig. 3. Creation of the golden standard by manually labelling the cow pixels in the frame. Green pixels represent the cow shape and are clearly distinguishable from the background (non-green pixels). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Multimodal Technologies and Interaction

MDPI

Article

A Wearable Sensor System for Lameness Detection in Dairy Cattle †

Juan Haladjian [1,*], Johannes Haug [1], Stefan Nüske [2] and Bernd Bruegge [1]

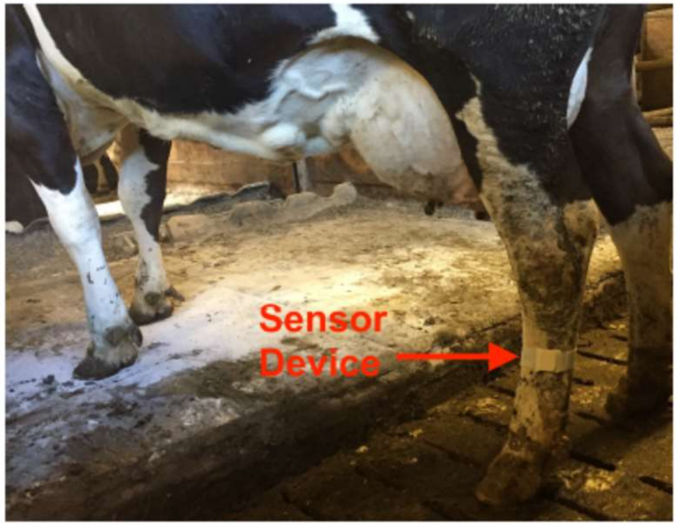
1. Lehrstuhl für Angewandte Softwaretechnik, Faculty of Informatics, Technical University Munich, Bolzmannstr 3, 85748 München, Germany; johannes.haug@tum.de (J.H.); bruegge@in.tum.de (B.B.)
2. Lehr- und Versuchsgut Oberschleißheim, Faculty of Veterinary Medicine, Ludwig Maximilian University, St. Hubertusstraße 12, 85764 München, Germany; stefan.nueske@lmu.de

* Correspondence: haladjia@in.tum.de; Tel.: +49-89-289-18235

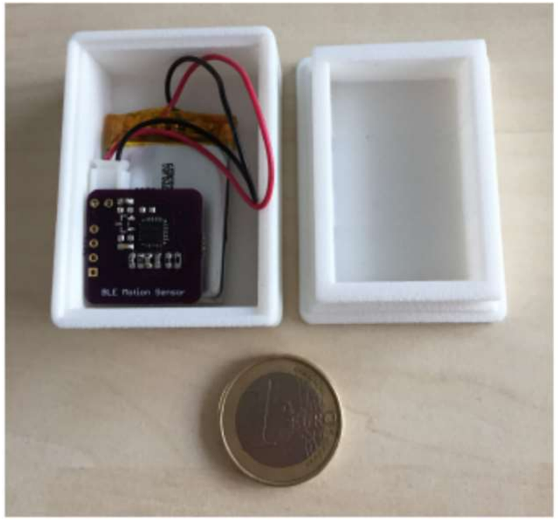
† This paper is an extended version of our paper published in the Fourth International Conference on Animal-Computer Interaction, Milton Keynes, United Kingdom, 21–23 November 2017.

check for updates

Received: 17 April 2018; Accepted: 8 May 2018; Published: 15 May 2018



(a)



(b)

Figure 1. Motion sensor attached to a cow's hind left leg taken from [4,5] (a) and sensor box (b).

UNIVERSITÀ DEGLI STUDI DI PERUGIA

Use of force sensors to detect and analyse lameness in dairy cows

M. Kujala, M. Pastell, T. Soveri

Force sensors were used to detect lameness in dairy cows in two trials. In the first trial, leg weights were recorded during approximately 12,000 milkings with balances built into the floor of the milking robot. Cows that put less weight on one leg or kicked frequently during milking were checked first with a locomotion scoring system and then with a clinical inspection. A locomotion score of more than 2 was considered lame, and these cows' hooves were examined at hoof trimming to determine the cause and to identify any hoof lesions. In the second trial 315 locomotion scores were recorded and compared with force sensor data. The force sensors proved to be a good method for recognising lameness. Computer curves drawn from force sensor data helped to find differences between leg weights, thus indicating lameness and its duration. Sole ulcers and white line disease were identified more quickly by force sensors than by locomotion scoring, but joint problems were more easily detected by locomotion scoring.

A.D. 1308 unipg UNIVERSITÀ DEGLI STUDI DI PERUGIA

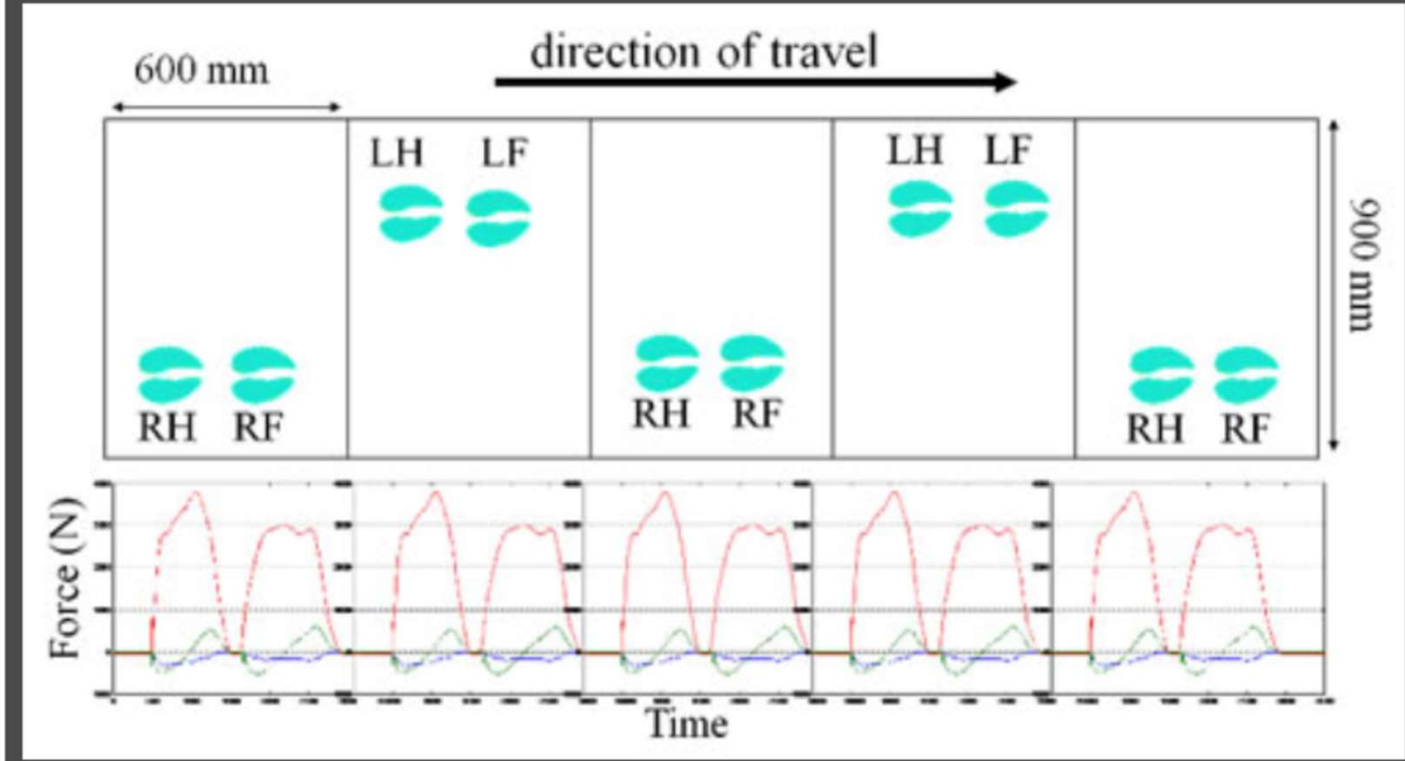
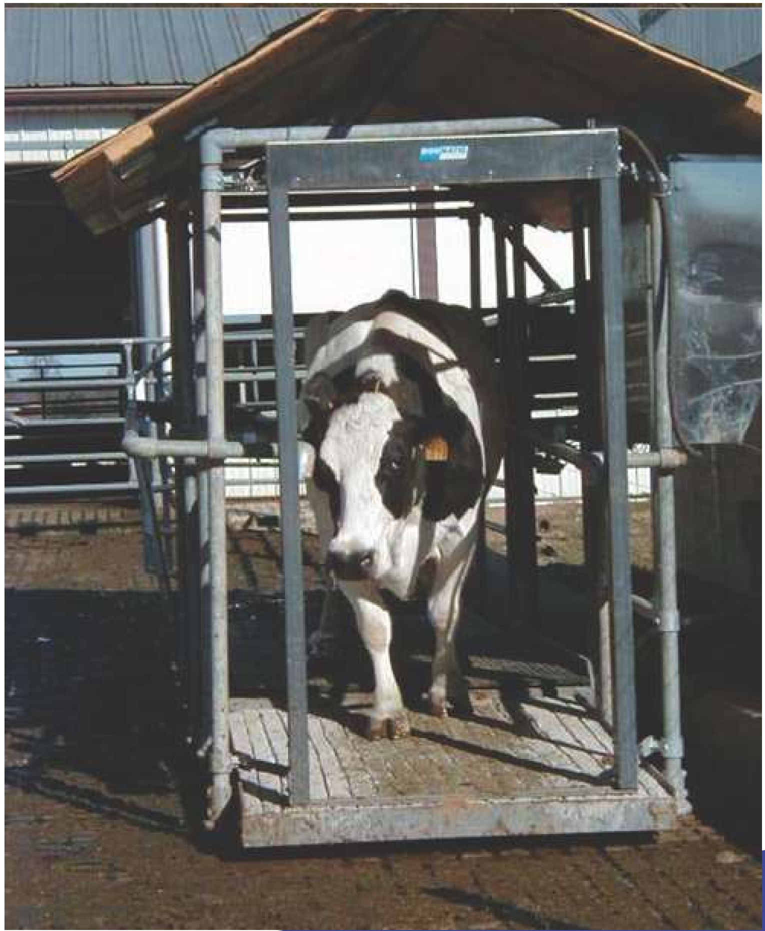


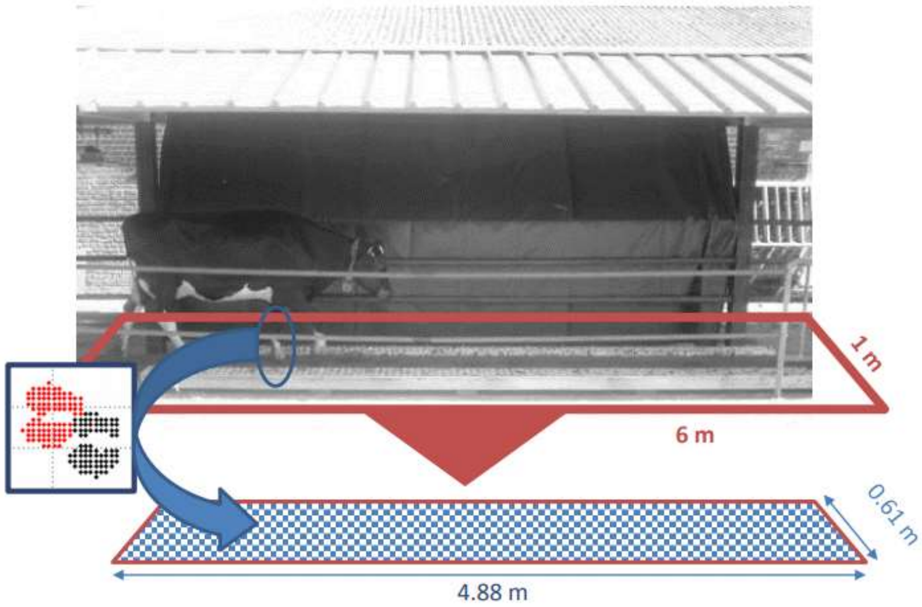
Figure 2: Schematic drawing of an 'ideal' data record, where each of the 5 force plates registers a foot strike of a front limb followed by a hind limb of the same side.



- System *reaction force detection* (RFD) (Tasch e Rajkondawar, 2004)

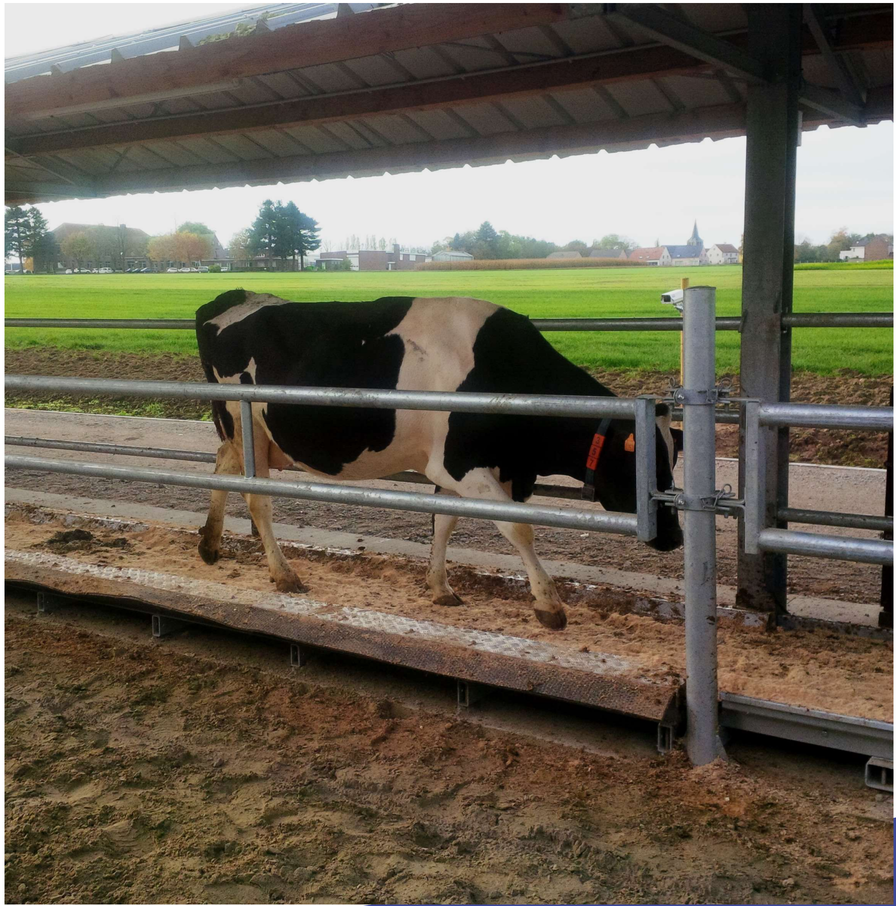
https://www.researchgate.net/scientific-contributions/39248884_PG_Rajkondawar

Monitoring cow gait



TIME – LOCATION – FORCE

http://www.dairycareaction.org/uploads/2/4/2/6/24266896/4.2_van_nuffel.pdf



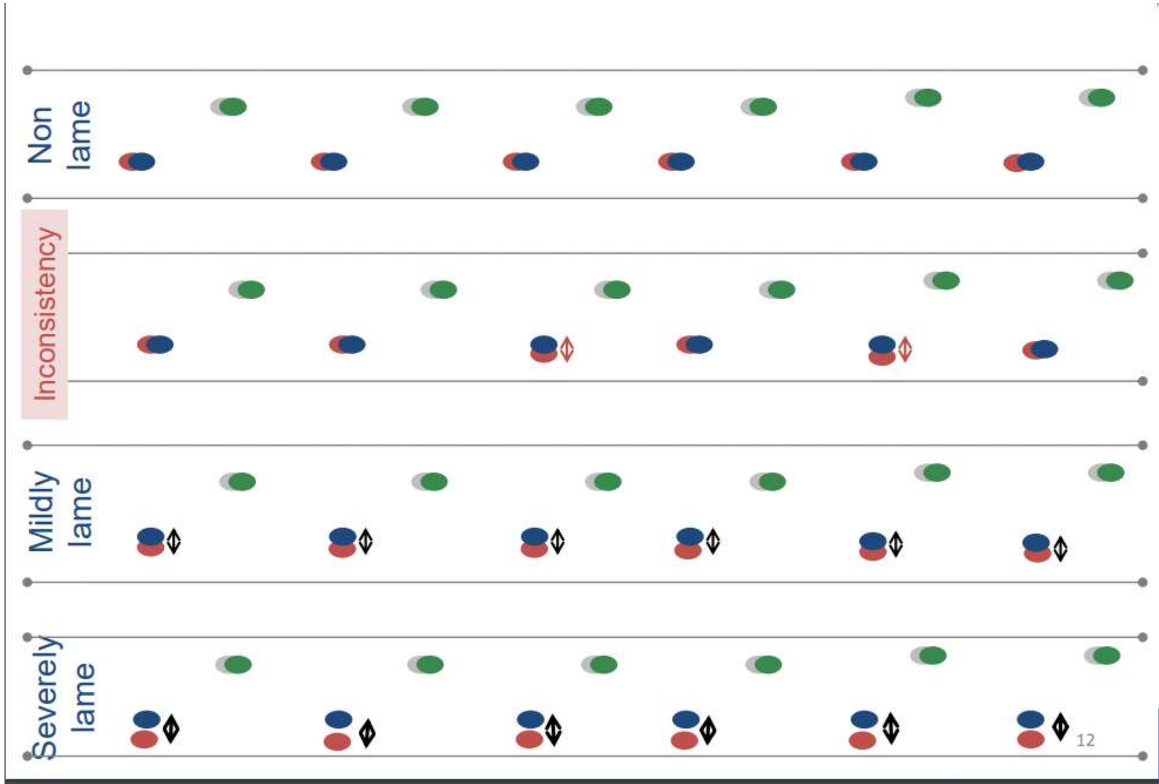
https://isense.farm/content/gaitwise

A.D. 1308
unipg
UNIVERSITÀ DEGLI STUDI
DI PERUGIA

Monitoring cow gait

10 Specific variables

- → Stride length
- → Stride time
- → Stance time
- → Step Overlap
- → Abduction
- → Asymmetry in
  - Stepwidth
  - Steplength
  - Steptime
  - Stancetime
  - Force



Variables of gait inconsistency

A.D. 1308
unipg
UNIVERSITÀ DEGLI STUDI DI PERUGIA

Computers and Electronics in Agriculture 158 (2019) 241–248

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

ELSEVIER

Original papers

Sheep lameness detection from individual hoof load☆

D.T. Byrne[a,b], H. Esmonde[c], D.P. Berry[a], F. McGovern[b], P. Creighton[b], N. McHugh[a,*]

[a] Animal & Grassland Research and Innovation Centre, Teagasc, Moorepark, Fermoy, Co. Cork P61 P302, Ireland
[b] Animal & Grassland Research and Innovation Centre, Teagasc, Mellows Campus, Athenry, Co. Galway H65 R718, Ireland
[c] Dublin City University, Glasnevin, Dublin 9, Co. Dublin D09 Y5N0, Ireland

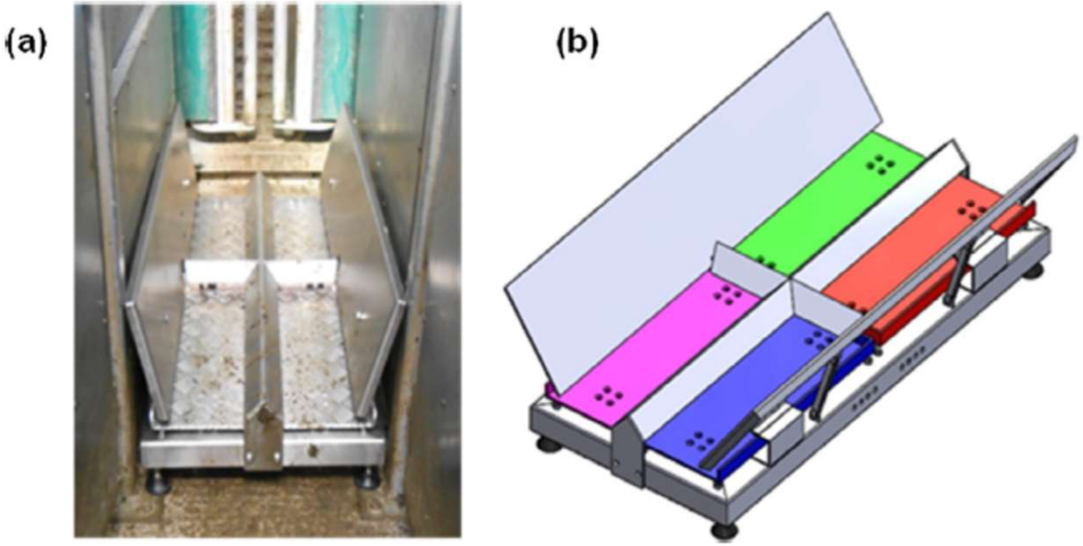


Fig. 1. (a) An image of the hoof weigh crate in the sheep raceway, and (b) an isometric view of the 3D model of the hoof weigh crate with each load platform a different color.

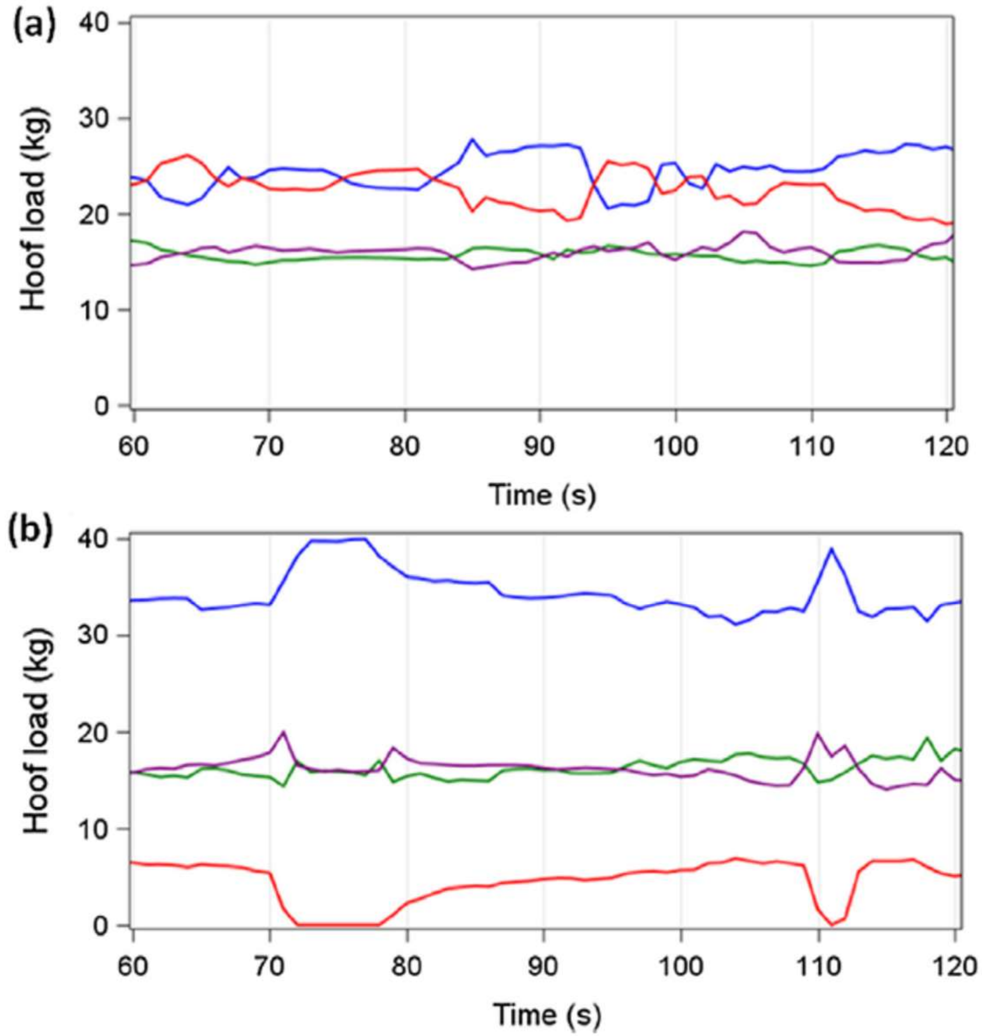


Fig. 3. The hoof load distribution [right front hoof (—), left front hoof (—), right back hoof (—) and left back hoof (—)] of (a) a ewe with four healthy hooves and (b) a ewe with extensive inter-digital dermatitis (i.e., score = 2) in the left front hoof.

A.D. 1308
unipg
UNIVERSITÀ DEGLI STUDI
DI PERUGIA

Computers and Electronics in Agriculture 136 (2017) 140–146

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

Original papers

Development of an early detection system for lameness of broilers using computer vision

A. Aydin

Department of Agricultural Machinery and Technologies Engineering, Faculty of Agriculture, Canakkale Onsekiz Mart University, 17020 Canakkale, Turkey

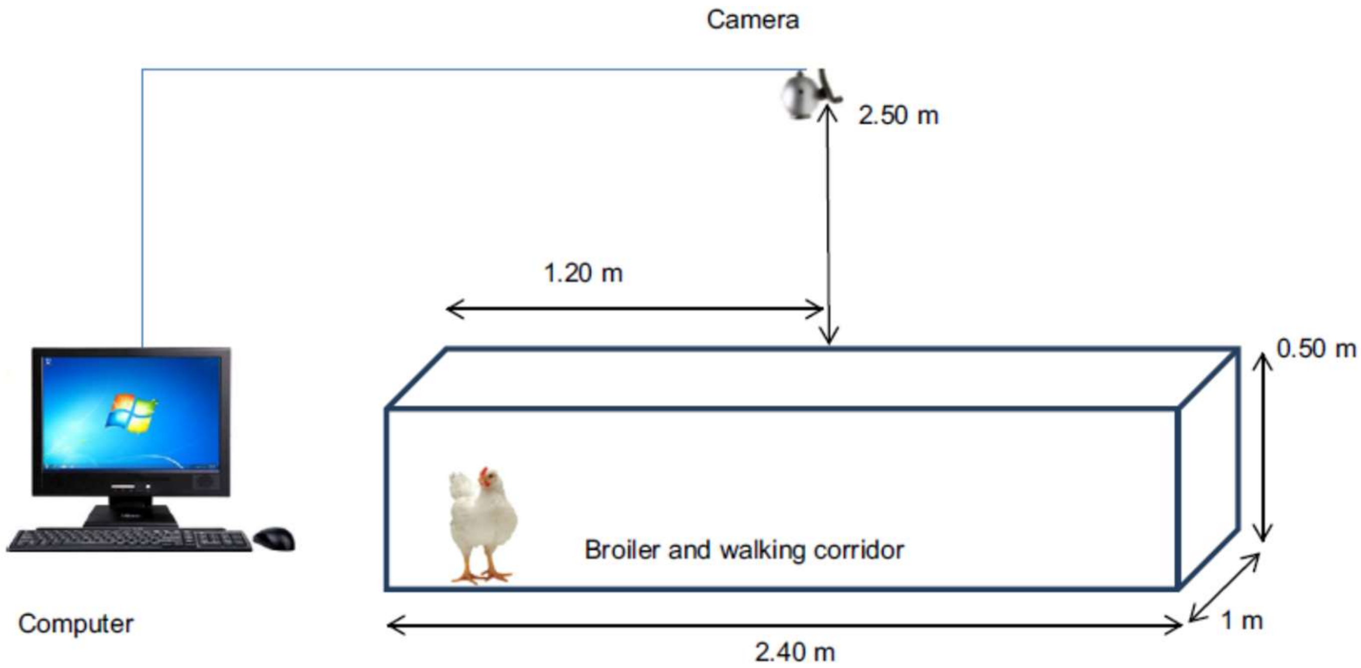


Fig. 1. The experimental setup and video recording equipment.

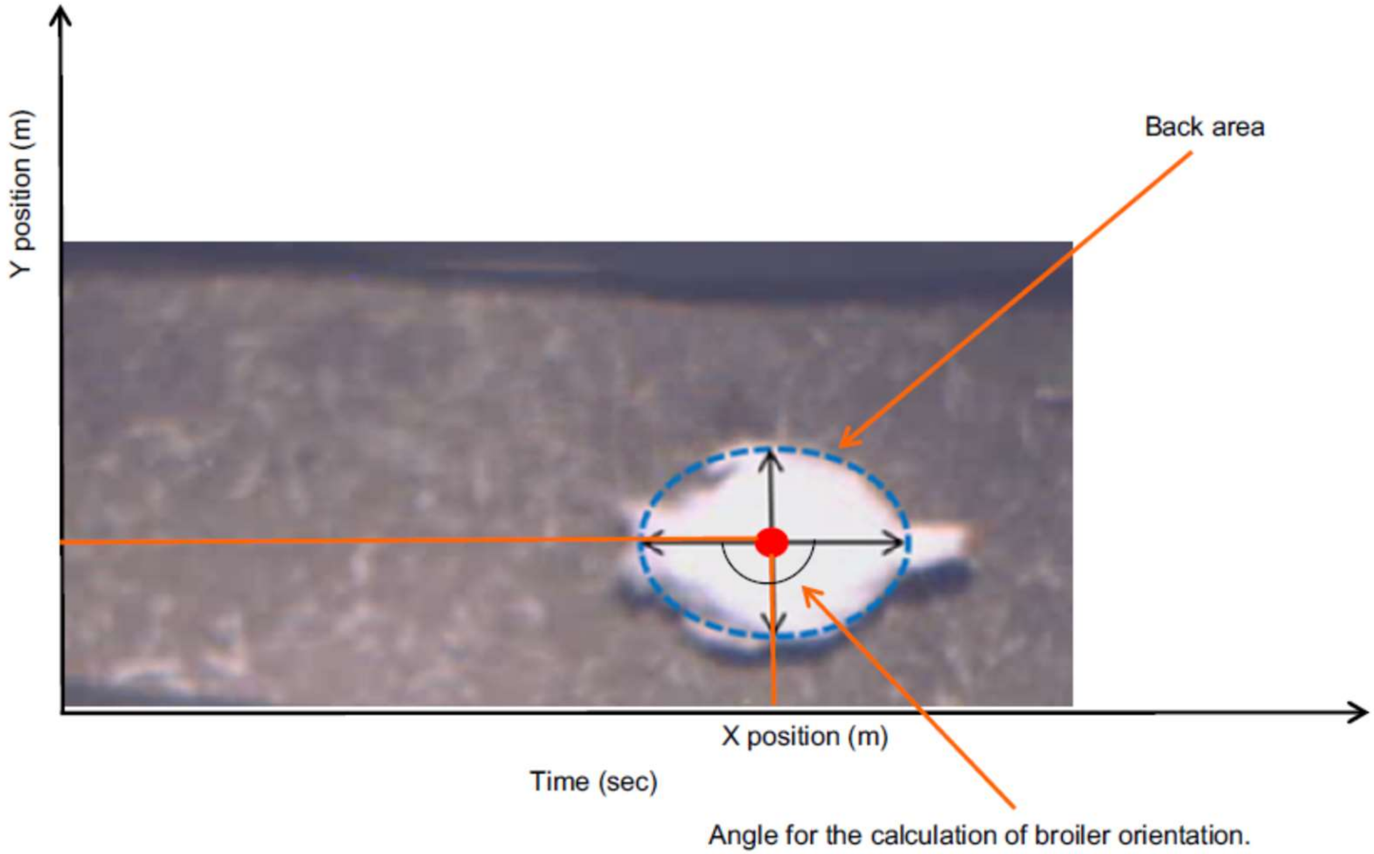
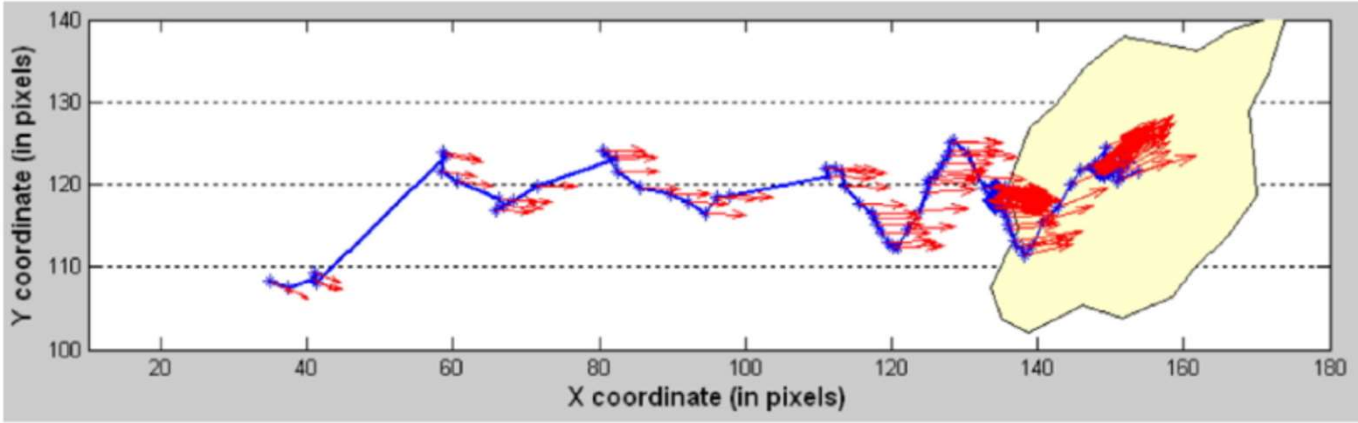
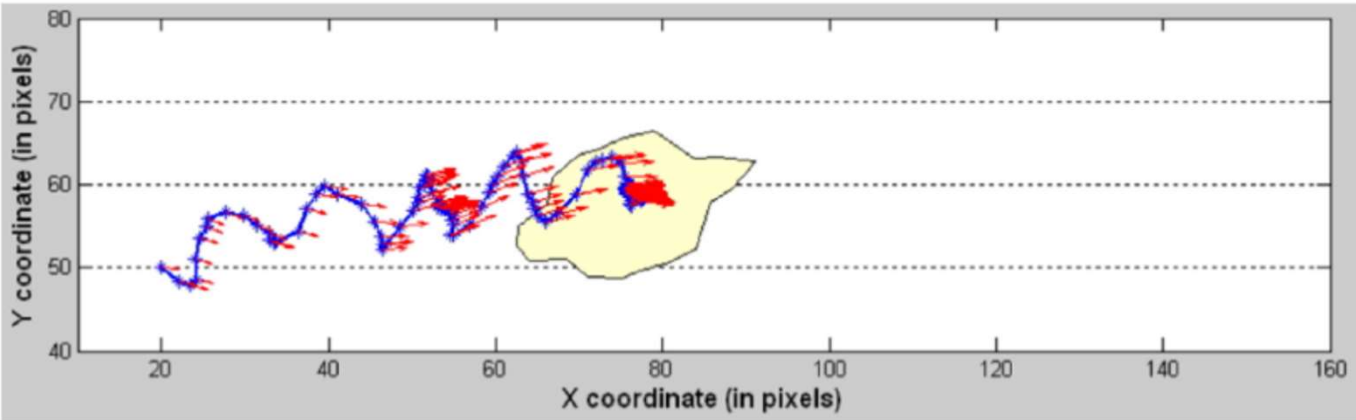


Fig. 2. Back area, orientation and x, y coordinates of the centre of the image of broiler.



(a) Gait Score 1



(b) Gait Score 4

UNIVERSITÀ DEGLI STUDI DI PERUGIA

Vol.3, No.3, 254-260 (2013)
http://dx.doi.org/10.4236/ojas.2013.33038

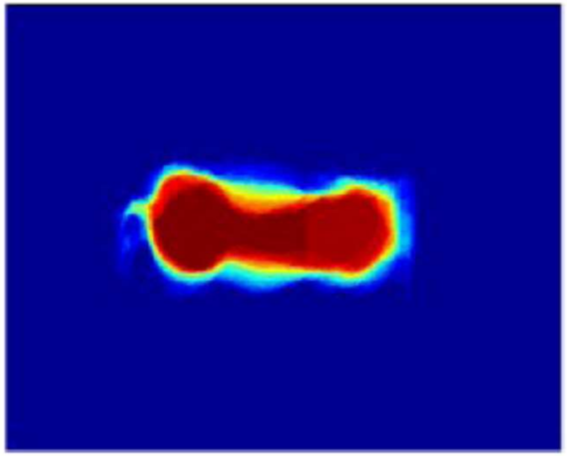
Open Journal of Animal Sciences

Development of a computer vision system to monitor pig locomotion

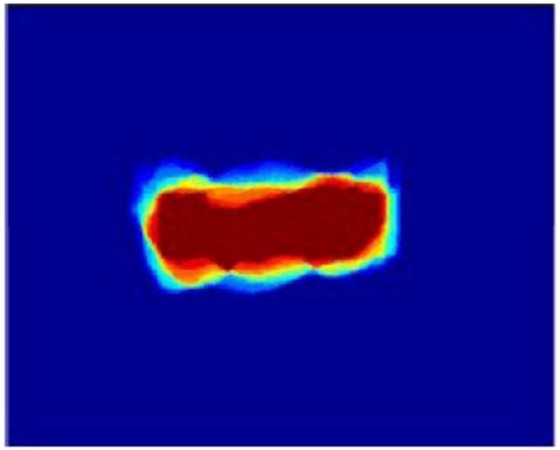
Jørgen Kongsro

Norsvin, Hamar, Norway; jorgen.kongsro@norsvin.no

Received 9 April 2013; revised 13 May 2013; accepted 3 June 2013



(a)



(b)

Figure 5. Map images of positive (a) and negaTive; (b) score PC1.

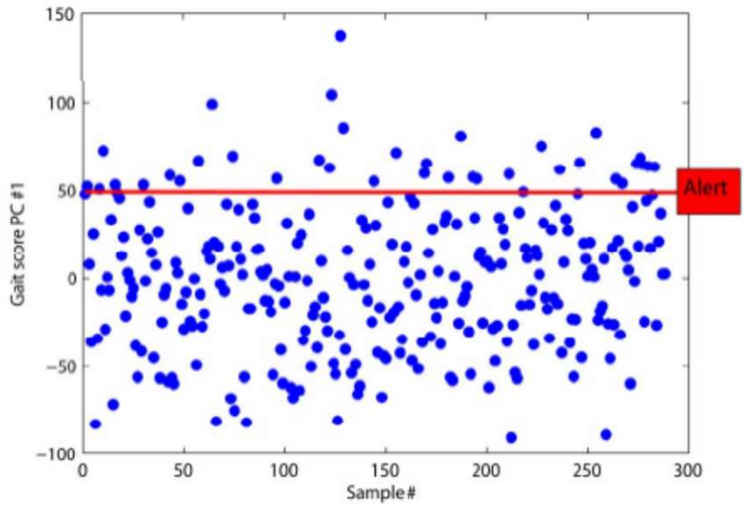


Figure 9. Possible application for VIA. Abnormal gaitalert.

Computers and Electronics in Agriculture 117 (2015) 1–7

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

ELSEVIER

journal homepage: www.elsevier.com/locate/compag

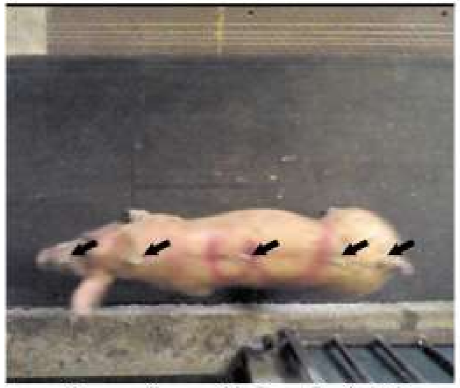
Validity of the Microsoft Kinect sensor for assessment of normal walking patterns in pigs

Sophia Stavrakakis [a,*], Wei Li [b], Jonathan H. Guy [a], Graham Morgan [b], Gary Ushaw [b], Garth R. Johnson [c], Sandra A. Edwards [a]

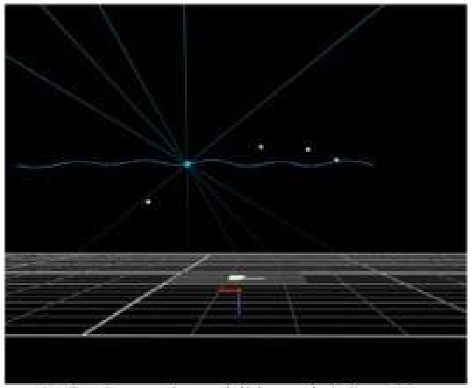
[a] *School of Agriculture, Food and Rural Development, Newcastle University, NE1 7RU, UK*
[b] *School of Computing Science, Newcastle University, NE1 7RU, UK*
[c] *School of Mechanical and Systems Engineering, Newcastle University, NE1 7RU, UK*

(A)

Gait lab set-up showing the Vicon cameras with infrared strobe around each lens, and the Kinect camera mounted above the walkway (arrow).



(B) Pig on walkway with five reflective Vicon markers (arrows) visible on the Kinect RGB camera.



(C) Reflective markers visible on the Vicon Nexus software motion capture screen. In this image the trajectory of the neck marker is displayed.

(D) The 30mm neck marker (arrow) extracted by a custom-written Kinect algorithm.

A.D. 1308 unipg UNIVERSITÀ DEGLI STUDI DI PERUGIA

PLOS | ONE

RESEARCH ARTICLE

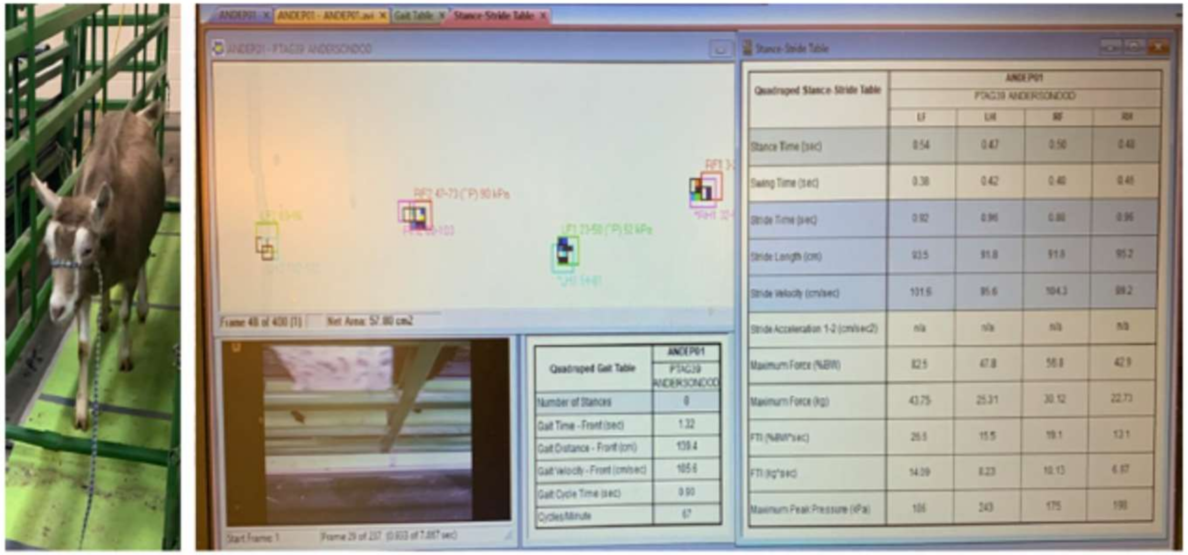
Use of a pressure-sensing walkway system for biometric assessment of gait characteristics in goats

Rebecca E. Rifkin[1 *], Remigiusz M. Grzeskowiak[1☯], Pierre-Yves Mulon[1‡], H. Steve Adair[1‡], Alexandru S. Biris[2‡], Madhu Dhar[1‡], David E. Anderson[1☯]

1 Department of Large Animal Clinical Sciences, University of Tennessee College of Veterinary Medicine, Knoxville, Tennessee, United States of America, 2 Center for Integrative Nanotechnology Sciences, University of Arkansas at Little Rock, Little Rock, Arkansas, United States of America

☯ These authors contributed equally to this work.
‡ These authors also contributed equally to this work.
* rrifkin1@utk.edu

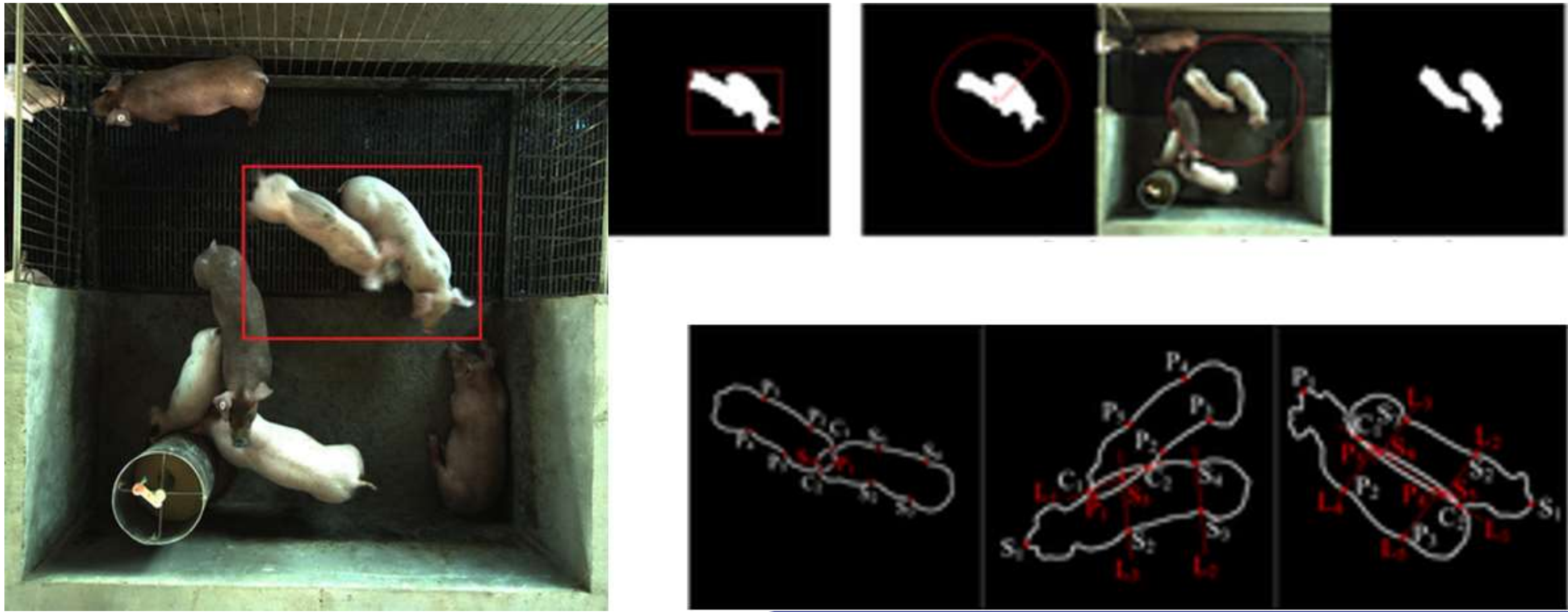
Check for updates



(A) (B)

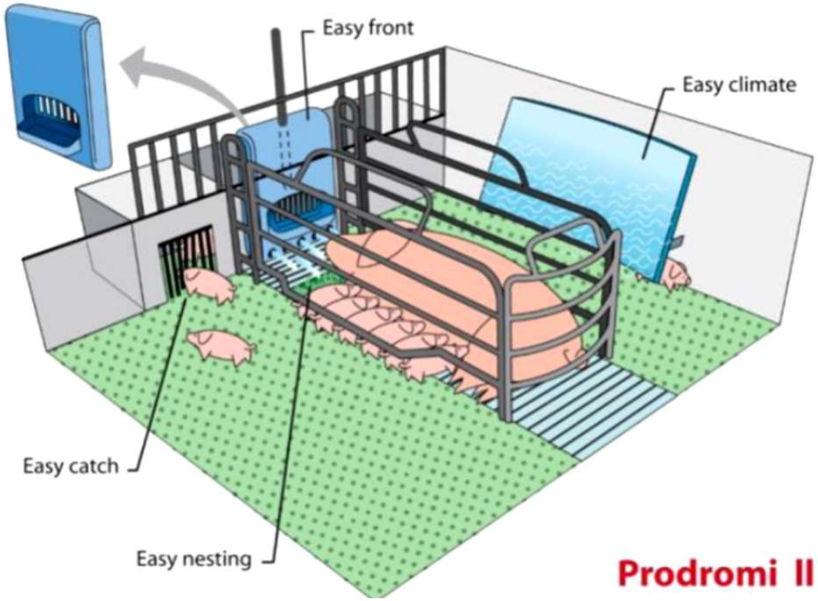
Fig 1. Examples of halter-lead training and sample gait analysis. (A) Pressure-sensing walkway placed in an alleyway system with soft mats and loose halter and lead for training. (B) Example of gait analysis with goat walking across pressure- sensing matrix placed in the alleyway system in the lower left-hand corner. The video recording with strike boxes is present in the upper left-hand corner, the stride stable is visible on the right, and the gait table is visible in the lower middle.

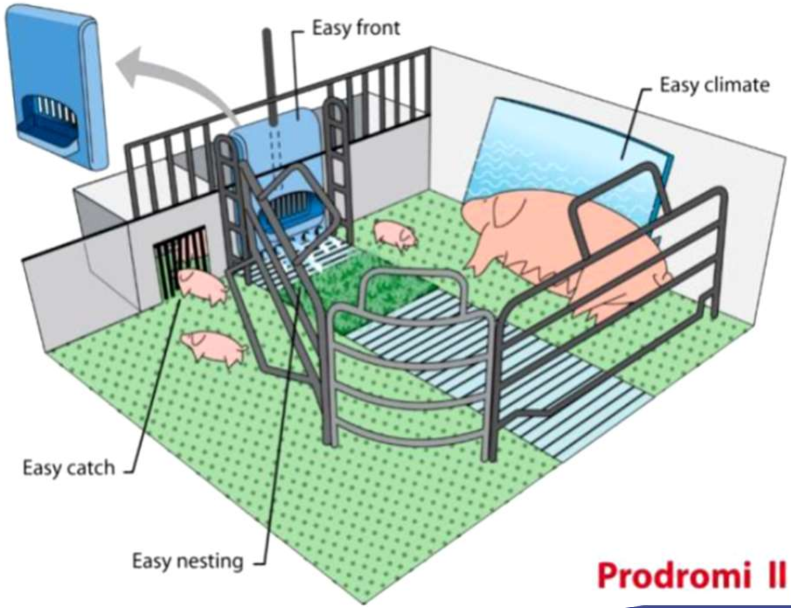
Automatic recognition of aggressive behaviors in pigs based on image analysis



KU Leuven

Use of litter for nest building





in the first 4 days

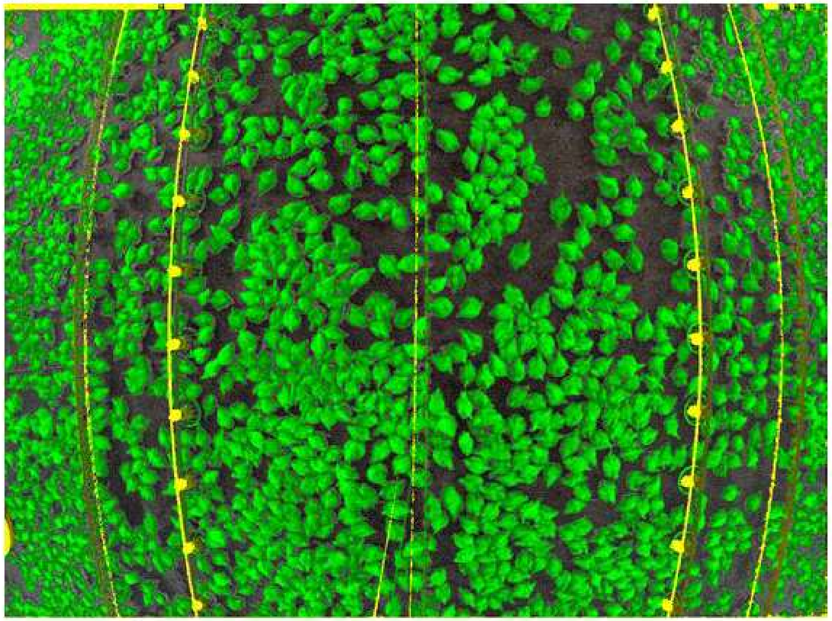
Sound

Byrne, 2017

Behaviour poultry

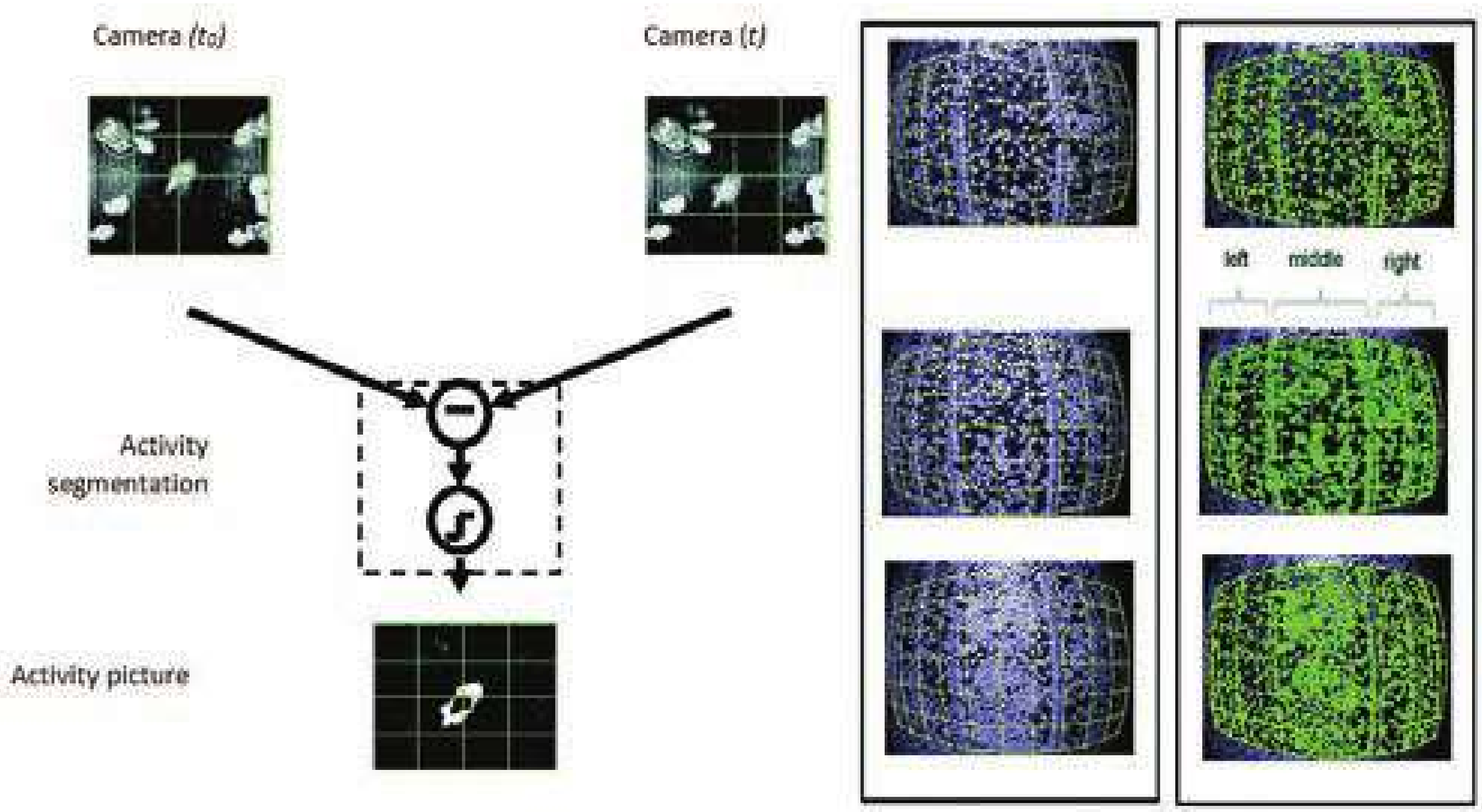
Behaviour poultry

- Detecting malfunctioning in broiler houses
- Produce alarms in real-time when malfunctioning happens (in feeder or drinker lines, light, climate control, etc.)



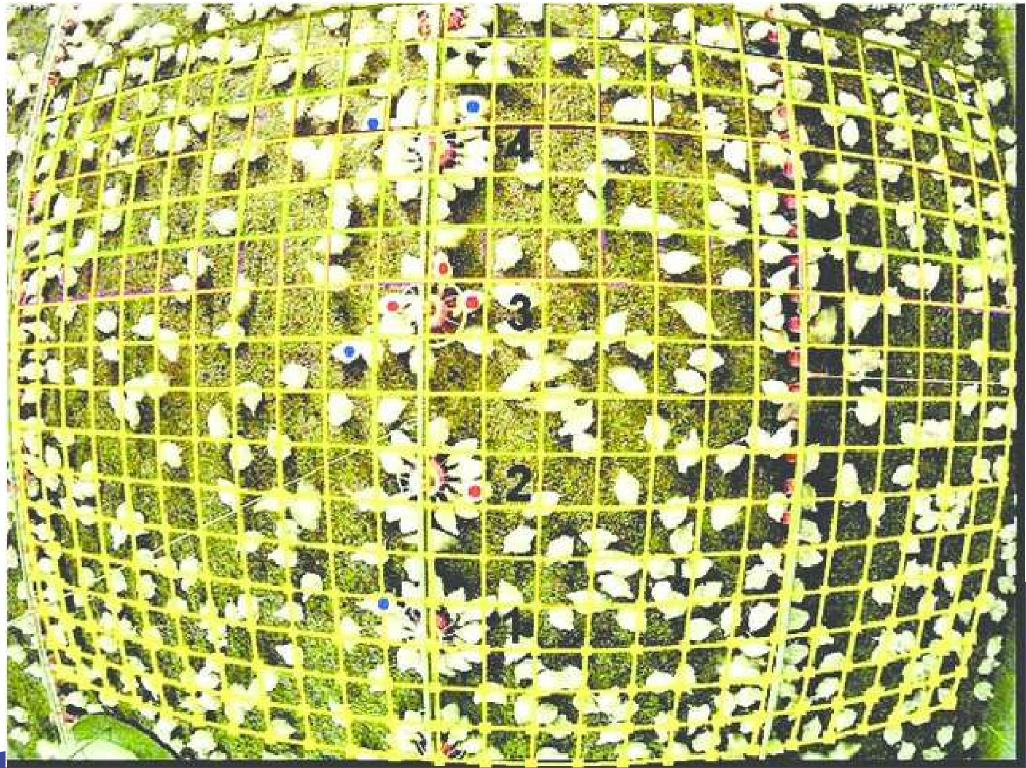
Berckmans (2013)

Welfare of broilers monitored through camera-based technology



De Montis et al., 2013

Feeding behavior around the pans: red points correspond to eating and blue points to not eating animals.

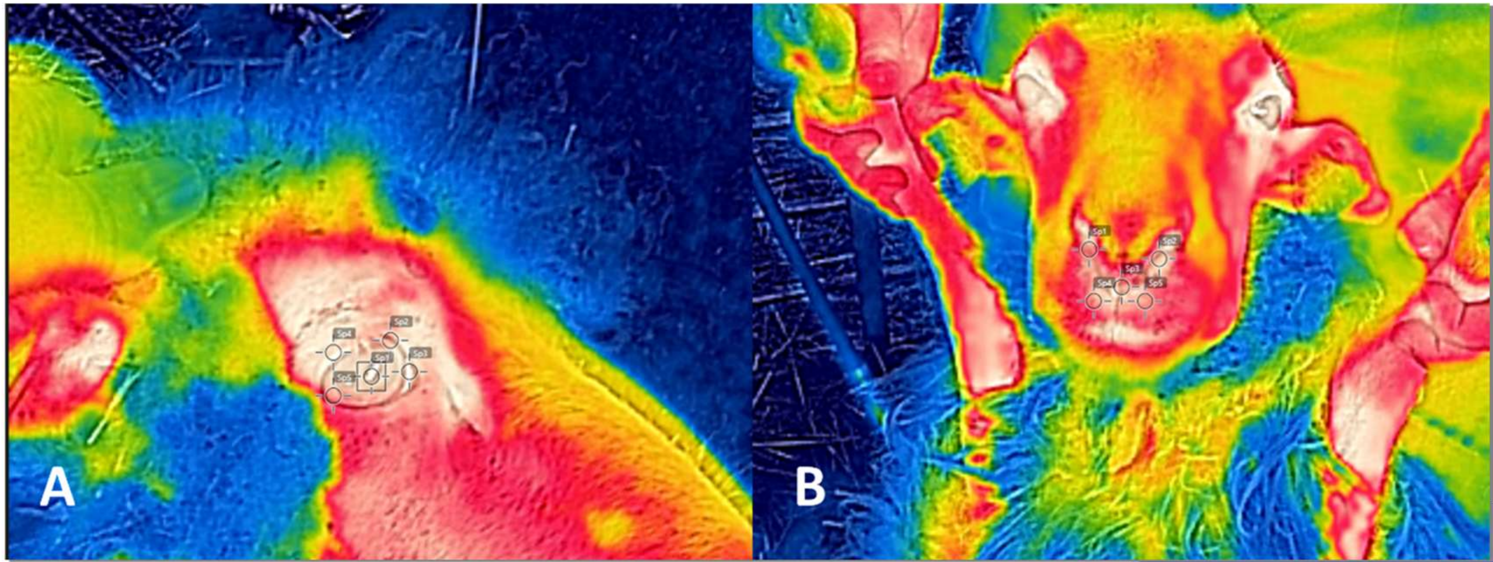


De Montis et al., 2013


Fancom
forward thinking
Welfare®
Quality

Welfare Quality parameter	***Measures***	***score 1-3***
Abs[illegible] prolonged hunger	Feed intake	2.6
	Feed availability	3.0
	Occupation density in feeding zones (eYeNamic)	3.0
	Duration feed alarm	1.0
Absense of prolonged thirst	Water intake	2.3
	Water availability	3.0
	Occupation density in drinking zones (eYeNamic)	3.0
	Duration water alarm	3.0
Comfort around resting	Duration darkness period	3.0
	Litter quality	1.7
	Occupation density in resting zones (eYeNamic)	2.3
Thermal comfort	Temperature within comfort zone	1.5
	Humidity within comfort zone	3.0
	CO2 concentration within comfort zone	3.0
Ease of movement	Average activity index (eYeNamic)	2.2
	Average distribution index (eYeNamic)	2.6
Absence of diseases	Mortality	1.0

Using Infrared Thermal Imaging to measure eye and muzzle temperature to assess stress in sheep.



Almeida et al., 2018

Lewis Baida et al. Anim Biotelemetry (2021) 9:4
https://doi.org/10.1186/s40317-020-00225-9

Animal Biotelemetry

UNIVERSITÀ DEGLI STUDI DI PERUGIA

REVIEW Open Access

Technologies for the automated collection of heat stress data in sheep

Bobbie E. Lewis Baida[1*], Alyce M. Swinbourne[1], Jamie Barwick[2], Stephan T. Leu[1] and William H. E. J. van Wettere[1]

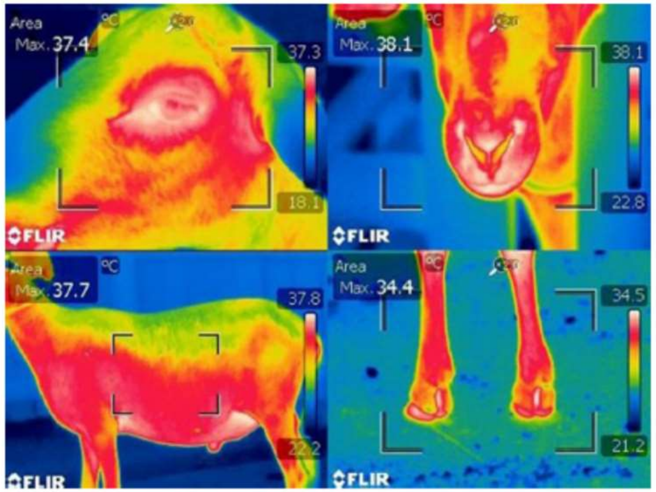


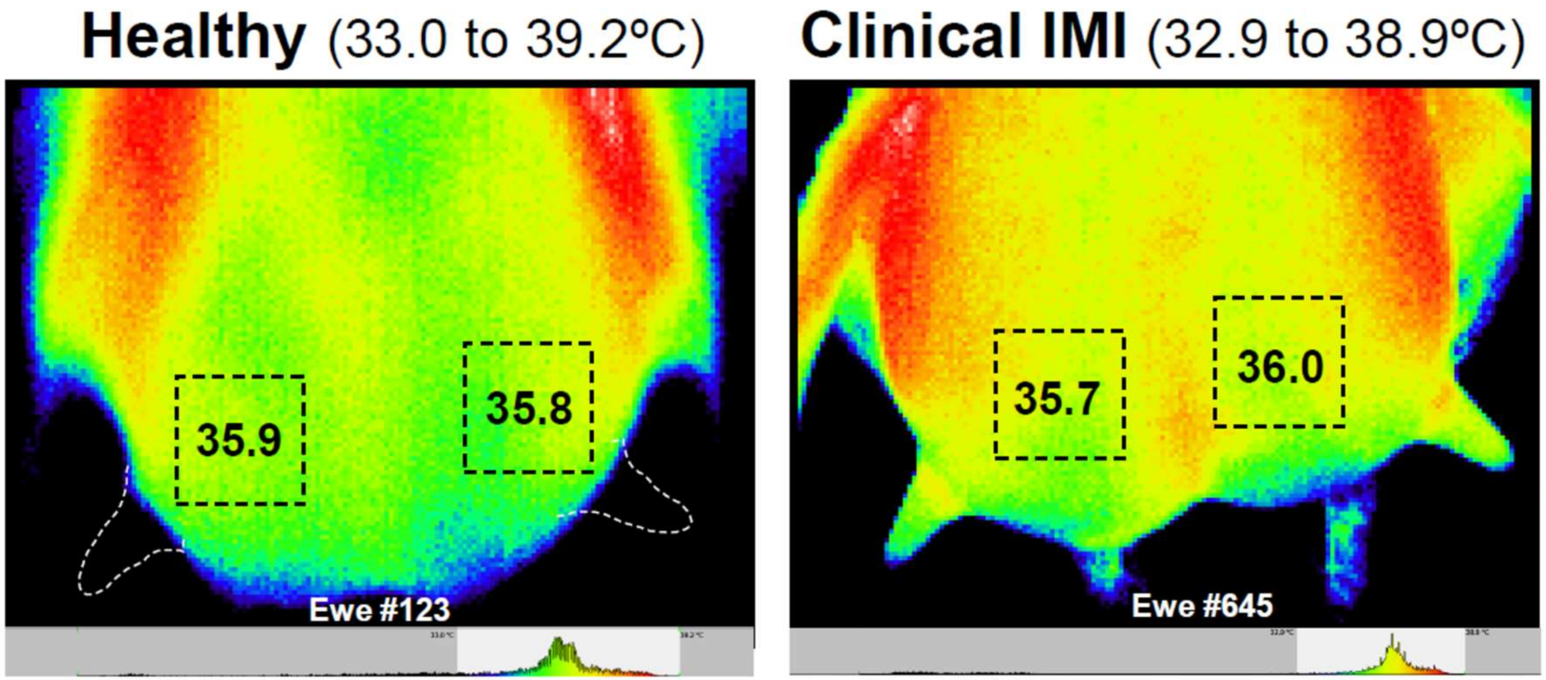
Fig. 3 Temperature gradients of specific regions of a sheep using infrared thermography. Sourced with permission from McManus et al. [74]

J. Dairy Sci. 97:1377–1387
http://dx.doi.org/10.3168/jds.2013-6978

UNIVERSITÀ DEGLI STUDI DI PERUGIA

Thermographic variation of the udder of dairy ewes in early lactation and following an *Escherichia coli* endotoxin intramammary challenge in late lactation

A. Castro-Costa,* G. Caja,*[1] A. A. K. Salama,*† M. Rovai,* C. Flores,* and J. Aguiló‡
*Grup de Recerca en Remugants (G2R), Departament de Ciència Animal i dels Aliments, Universitat Autònoma de Barcelona, 08193 Bellaterra, Spain
†Sheep and Goat Research Department, Animal Production Research Institute, 12311 Dokki, Giza, Egypt
‡Departament de Microelectrònica i Sistemes Electrònics, Universitat Autònoma de Barcelona, 08193 Bellaterra, Spain



A.D. 1308 unipg UNIVERSITÀ DEGLI STUDI DI PERUGIA

Work Smarter, Not Harder: Goat Handling

Categories: Farming & Homesteading

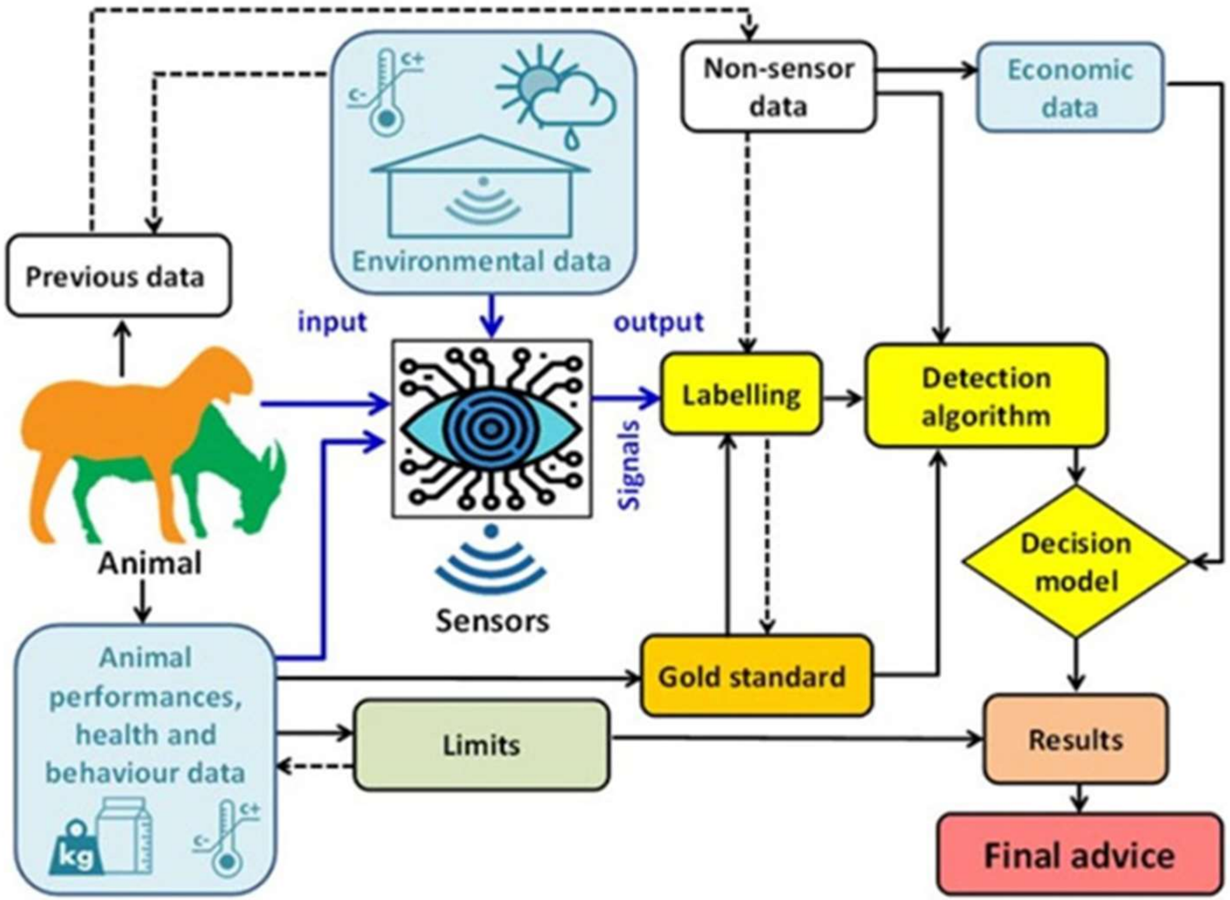


Fig. 1. Precision livestock farming solutions for small ruminants. (a): Generalized scheme showing flow of information from sensor data to the final decision support solution.

Caja et al., 2020

A.D. 1308
unipg
UNIVERSITÀ DEGLI STUDI
DI PERUGIA

Computers and Electronics in Agriculture 185 (2021) 106127

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

ELSEVIER

Original papers

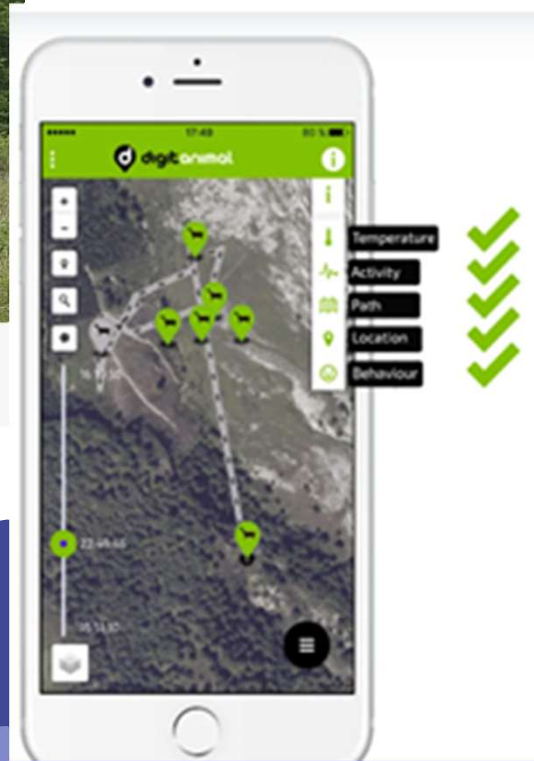
RetIS: Unique Identification System of Goats through Retinal Analysis

Subhranil Mustafi *, Pritam Ghosh, Satyendra Nath Mandal

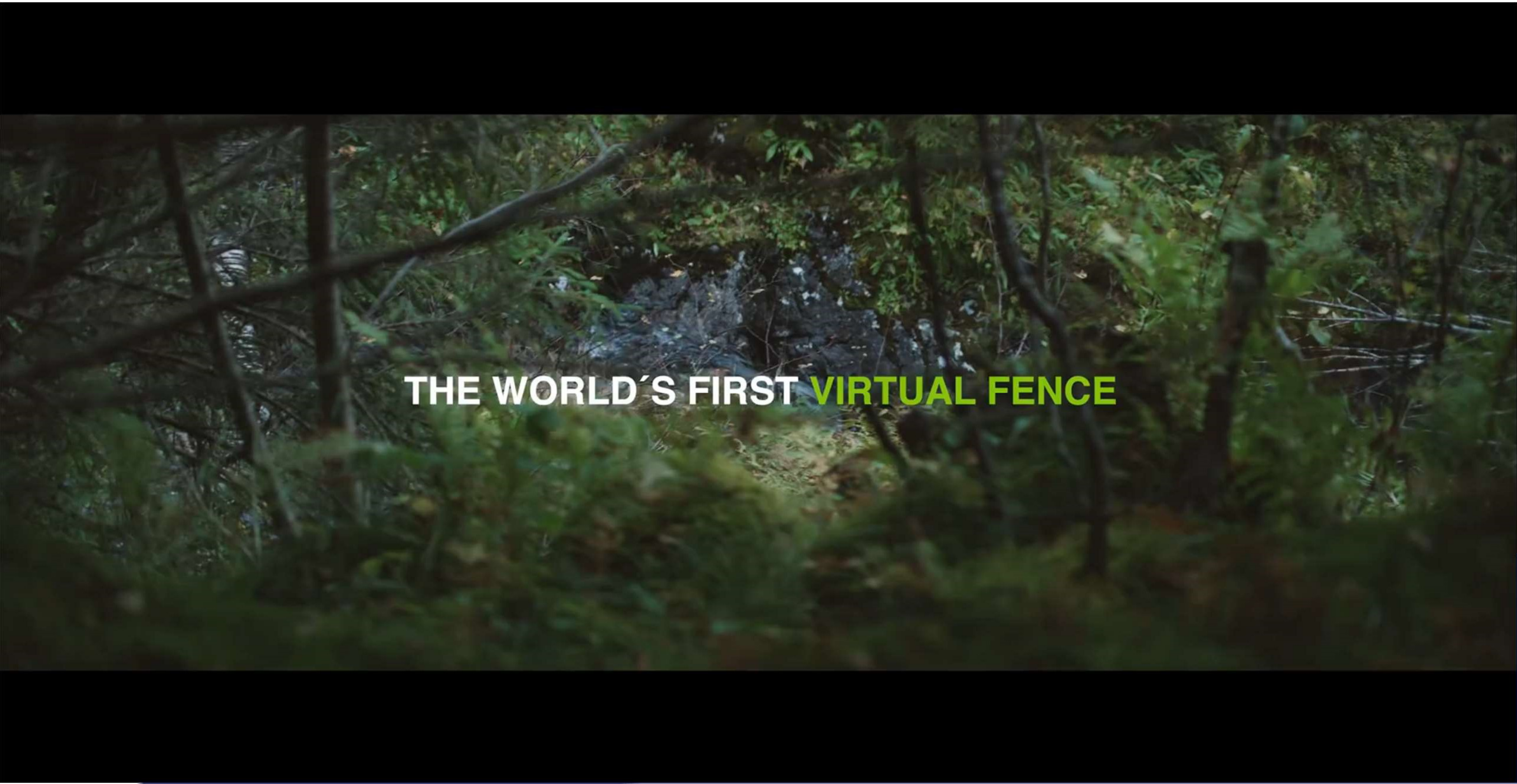
Department of Information Technology, Kalyani Government Engineering College, Kalyani 741235, India

fication, otherwise the templates belong to two separate individual goats. This model has been tested with more than 200 retinal images obtained from twelve different goats producing 99% accuracy. The performance of this proposed model has been compared with other animal identification technologies and is found to be the most accurate and precise.

A.D. 1308
unipg
UNIVERSITÀ DEGLI STUDI DI PERUGIA



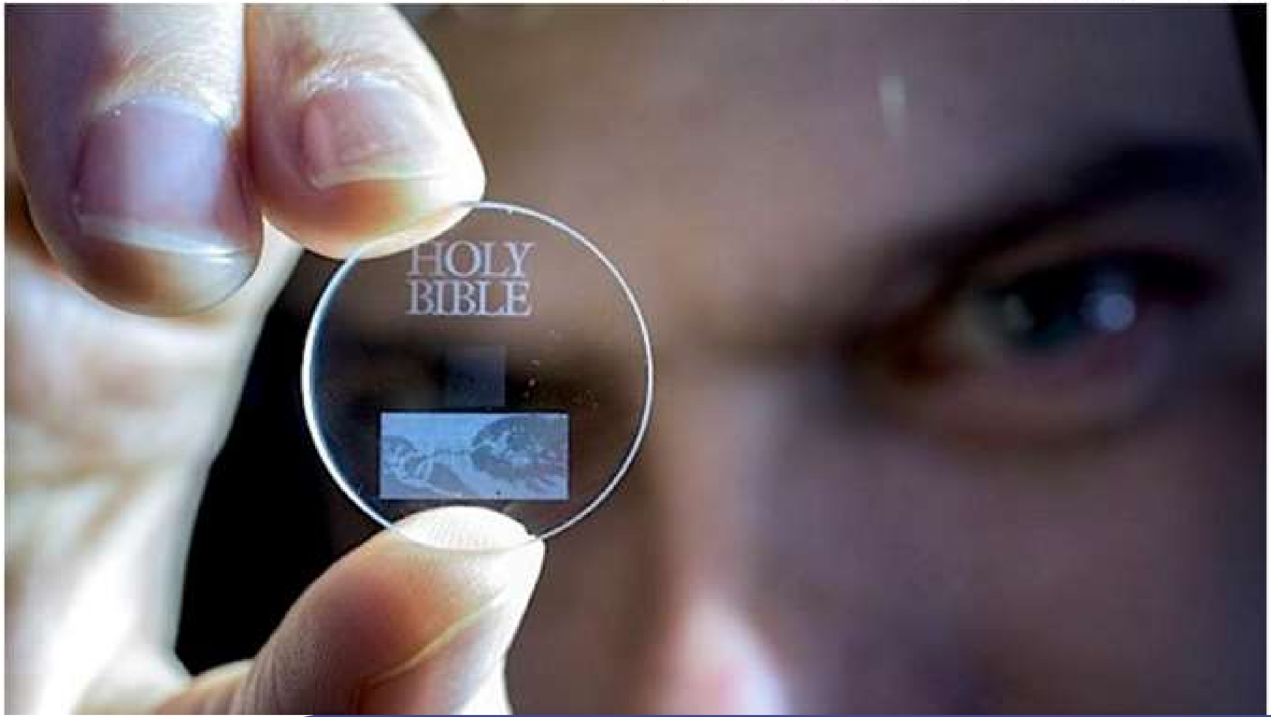
https://digitanimal.com/goats/?lang=en


THE WORLD´S FIRST VIRTUAL FENCE

Future – Eternal 5D data storage could record the history of humankind.

The storage allows unprecedented properties including 360 TB/disc data capacity, thermal stability up to 1,000°C and virtually unlimited lifetime at room temperature (13.8 billion years at 190°C)

Optoelectronics Research Centre / University of Southampton



Technological development.
Bridging the data gap in farming: The promise of digital technologies

https://www.alltech.com/blog/bridging-data-gap-dairy-farming-promise-digital-technologies

The smartphone camera analyses the data continuously

Computers and Electronics in Agriculture 201 (2022) 107291

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

ELSEVIER

A.D. 1308 unipg UNIVERSITÀ DEGLI STUDI DI PERUGIA

5G in agri-food - A review on current status, opportunities and challenges

Check for updates

Mireille van Hilten *, Sjaak Wolfert

Wageningen Economic Research, Wageningen University & Research, The Netherlands

ARTICLE INFO

Keywords:
6G
Connectivity
Agriculture
Food systems
Digital transformation

ABSTRACT

Autonomous tractors, spraying drones, robotics and fully autonomous farms are possible outcomes of the digital transformation trend in agriculture and food systems which is fostered by continuous technological advancement and the increasing connectivity capacity. These futuristic scenarios will be unlocked by 5G connectivity, the next step after 4G, because it enables high data transfer volumes and low latency which can lead to many beneficial outcomes for technology applications in agri-food, such as Internet of Things (IoT) and Blockchain. Considerable progress is seen in the 5G ecosystem around the world, from South Korea to Australia and Europe. This review presents the opportunities and challenges of 5G in agri-food. The six most compelling use cases of 5G in agri-food at this moment from different parts of the world are in Brazil, the Netherlands, South Korea and the United Kingdom. The future of 5G in agri-food will depend on a number of enabling factors including interoperability, data governance and security, new business models, policy changes, and innovative ecosystems. The baseline scenario of connectivity and infrastructure for a region or country is determined by the dimensions of 5G aggregation-, cyber physical management- and decision-making levels, which guide future 5G applications in agri-food. Agriculture technology collaboration across the private and public sector and ecosystem development are the first steps for all countries to make progress towards large scale uptake of 5G in agri-food.

A.D. 1308 unipg UNIVERSITÀ DEGLI STUDI DI PERUGIA

Back in 1995, things were different!

Back in 1995, things were different!

Thank for your attention