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Extracting body surface dimensions from top-view images of pigs

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Abstract: Continuous live weight and carcass traits estimation are important for the pig production and breeding industry. It is widely known that top-view images of a pig's body (excluding its head and neck) reveal surface dimension parameters, which are correlated with live weight and carcass traits. However, because a pig is not constrained when an image is captured, the body does not always have a straight posture. This creates a big challenge when extracting the body surface dimension parameters, and consequently the live weight and carcass traits estimation has a high level of uncertainty. The primary goal of this study is to propose an algorithm to automatically extract pig body surface dimension parameters, with a better accuracy, from top-view pig images. Firstly, the backbone line of a pig was extracted. Secondly, lengths of line segments perpendicular to the backbone line were calculated, and then feature points on the pig's contour line were extracted based on the lengths variation of the perpendicular line segments. Thirdly, the head and neck of the pig were removed from the pig's contour by an ellipse. Finally, four length and one area parameters were calculated. The proposed algorithm was implemented in Matlab[®] (R2012b) and applied to 126 depth images of pigs. Taking the results of the manual labeling tool as the gold standard, the length and area parameters could be obtained by the proposed algorithm with an accuracy of 97.71% (SE=1.64%) and 97.06% (SE=1.82%), respectively. These parameters can be used to improve pig live weight and carcass traits estimation accuracy in the future work.

Keywords: body surface dimension, image analysis, skeleton, triangulated network, ellipse fitting

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1 Introduction

Pig's live weight and the value of pig carcass are both important for pig production and breeding industry. The weight of a pig is an important indicator of its growth and health, provides a valuable reference for production managers in maintaining nutrition and environment at a suitable level for the growing animals^[1-3]. The value of pig carcass for meat production depends primarily on the relative proportions of fat and lean. The shape of retail cuts and thus the carcass conformation plays an increasingly significant role in the meat production industry^[4]. Estimates of carcass traits and pig weight automatically and continuously during a pig's lifetime are invaluable for the pig breeder. According to the estimated carcass traits and weight information, breeders can adjust their management regime, such as breeding environment, nutrition, specification of a performance target, genotype choice,

and so on.

The concepts of relating pig body size and shape to pig weight and carcass traits are not new to the field of animal science^[5,6]. Five dimension parameters in pig body surface, as shown in Figure 1, have been used to estimate the pig's live weight and carcass traits. These parameters include one area parameter ($A4$) and four length ones ($L1$ to $L4$).

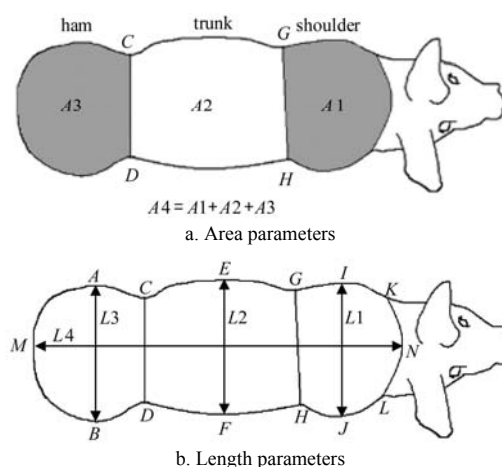


Figure 1 Body surface dimension parameters of a top-view pig image

As shown in Figure 1a, $A4$ is the total plane area of body, excluding head and neck. $A4$ is the sum of $A1$, $A2$, and $A3$. Where, $A1$ is the plane area of shoulder, cranial to line segment GH . $A2$ is the plane area of trunk, between line segment GH and CD . $A3$ is the plane area of ham, caudal to line segment CD . As

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shown in Figure 1b, $L1$ is the width of shoulder at its widest point. $L2$ is the width of trunk at its widest point. $L3$ is the width of ham at its widest point. $L4$ is the total length of body, excluding head and neck.

Previous works^[2,7,10-14] had estimated the live weight of a pig from top-view body area characters, such as $A4$, as shown in Figure 1a. Different approaches, such as spline functions^[15], linear regression^[2], artificial neural network^[3], transfer functions^[11], etc., had been used to express the relationship between $A4$ and the live weight of the pig.

As well as live weight estimation, several digital imaging techniques, such as computer tomography (CT) and magnetic resonance imaging (MRI), general camera imaging had been used to estimate pig body composition and carcass traits^[6,8,9]. From the cost perspective, carcass traits estimation based on general camera images has better prospects in application. Doeschl et al.^[6] suggested that pig body shape characters in a top-view image, such as $L1$ to $L4$ shown in Figure 1b, are useful in the estimation of muscle size, carcass conformation and composition. And the relationship between $L1$ to $L4$ and pig carcass traits was established.

The previous work mentioned above suggested that body dimension parameters ($L1$ to $L4$ and $A4$) extraction from pig top-view images with high accuracy is crucial to pig breeding. With the widespread use of information technology in precision livestock farming, researchers began to extract body dimension parameters by using image analysis, for pigs^[7,16,17], cows^[18,19], and broilers^[20].

There are some deficiencies in the existing researches^[7,16,17] on body dimension parameters extraction for pig images. Firstly, images with ideal pig posture were required. That is, pig back should be straight, without bending. Secondly, the arc segment used to cut the head and neck, say the arc KNL shown in Figure 1b, was determined by an ellipse fitted by the pig's whole contour, which could be influenced seriously by the pig's posture. That is, different posture could bring totally different arc segment, even for the same pig on the same day. Furthermore, parameters accuracies of the existing research were affected seriously by the variation in light condition, which is a common problem in image analysis area.

Liu et al.^[21] tried to improve the accuracy of the extracted dimension parameters by using two line segments determined by the three points in the backbone line of a pig. But even so, the two line segments could not represent pig's backbone line accurately, and the resulting feature points, such as points A to N in Figure 1b, were not accurate enough. Furthermore, Arc segment for pig head and neck cutting in Liu et al.^[21] was represented by a straight line segment located on pig neck area, which could bring a worse accuracy of parameters, such as $L4$ and $A4$.

Kashiha et al.^[11] used an image processing software developed by IMIX[®] (2009) to extract $L1$ to $L4$ and $A4$. It represented a pig's principal axis by the maximum length line segment inside the pig contour which passed through the grave center of the pig body image. Then, four feature points (points C , D , G , and H in Figure 1b) were extracted based on the concave and convex variation of the pig body between shoulder and ham. Based on the two central points of segment CD and GH , as shown in Figure 1, backbone line of a pig was determined by three line segments which are parallel to the principal axis. IMIX[®] software (referred to as IMIX from here on) adopted Bezier curve to cut pig head and neck. The curve was determined by the feature points I , J , and two lines

which were parallel to pig's principal axis and passes through I and J , respectively.

Similar with the method proposed by Liu et al.^[21], backbone line extracted by IMIX was represent by three line segments. The extracted feature points may shift from their actual position, especially for pigs with obvious curving body posture. At the same time, due to the limited information used in IMIX to determine the Bezier curve, there is still room for accuracy improvement for pig body surface dimension parameters.

In this paper, an algorithm, named by BSDPE (Body Shape Dimensions Parameters Extraction algorithm), is introduced to extract body surface dimension parameters ($L1$ to $L4$ and $A4$) from top-view pig images, captured by a Kinect camera, automatically. The main object of BSDPE is to extract the dimension parameters with a high accuracy, even for pigs with obvious curving body posture. BSDPE did not take the variation of light condition into account. That is because light condition variation has little impact on pig body extraction for images captured by a Kinect camera.

2 Materials and methods

To collect image data for the algorithm, a data collection step was firstly carried out to collect top-view images from a group of pigs under commercially conditions. The data collection set-up is described below.

2.1 Pigs and housing

Six grower pigs, 80-90 days old, Pietrain \times Topigs 20, were randomly selected from 'Laverdonk', the research farm of Agrifirm NV (CeHaVe, Heeswijk, the Netherlands), for the data collection in this research. The experiment lasted for ten days, from 24th March 2014 to 2nd April 2014. Six pigs were assigned to two fully slatted pens (2.85 m \times 3.60 m), each with three pigs. Each pen was equipped with a feeder and one drink nipple. Pigs had ad libitum access to feed and water.

2.2 Image system

The image system was comprised of a KINECT camera (Primesense, Carmine 1.08 3D sensor), RFID ear tags, a RFID reader (including an antenna), and a logging computer (DELL T3600), as shown in Figure 2. The KINECT camera was 2.28 m above the pen floor. The RFID reader, protected by a protection shield, was located on one of the metal side panels of the feeder. The distance of the two metal side panels was 0.45 m. A RFID tag was fitted on one ear of each pig. A pig was identified by the RFID ear tag value when it accessed the feeder. Once an ear tag value was obtained by the RFID reader, a command was sent to the logging computer by the RFID reader and the computer activated the KINECT camera to collect images of the pig.

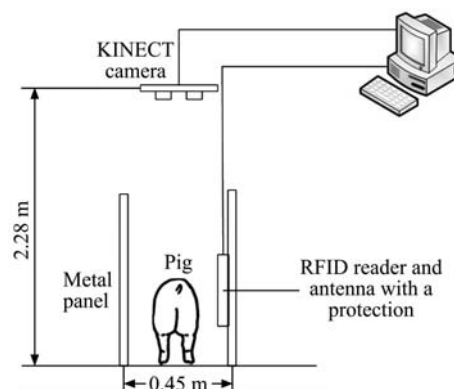


Figure 2 Schematic diagram of the image system used in this study

2.3 Manual labelling tool

Using the pig body surface dimension results extracted by manual labelling tool as the gold standard, the parameters accuracy of IMIX and BSDPE are compared. Manual labelling is accomplished by using a Matlab software which is developed by M3-BIORES (a research group focus on measure, model & manage bioresponses in KU Leuven). Top-view pig images are loaded into the software one by one. For each image, an experienced pig body shape analyst select feature points and pig contour without head by using a mouse. Then the software calculates dimension parameters ($L1$ to $L4$ and $A4$) automatically. A technique flow of the manual labelling tool is briefly introduced in Appendix 1.

2.4 Proposed algorithm- BSDPE

BSDPE comprises four steps: depth image pre-processing, pig's backbone line extraction, feature points extraction, and body surface dimension parameters calculation.

2.4.1 Image pre-processing

The input of BSDPE is a depth image captured by a KINECT camera, as shown in Figure 3b. Different color in a depth image corresponds to different distance between an object and the KINECT camera. The original RGB image and the grayscale processing result of Figure 3b are shown in Figure 3a and Figure 3c, respectively. After a binary processing by using Otsu's method^[22], besides the pig, part of the feeder and body of other pigs are extracted as the foreground objects, as shown in Figure 3d.

A binary image with the pig only, as shown in Figure 3e, is acquired by extracting the largest connected region of Figure 3d. Then, morphological processing is carried out to remove holes and spindly parts in the binary image. The morphological processing and edge detection results of Figure 3e are shown in Figures 3f and 3g, respectively.

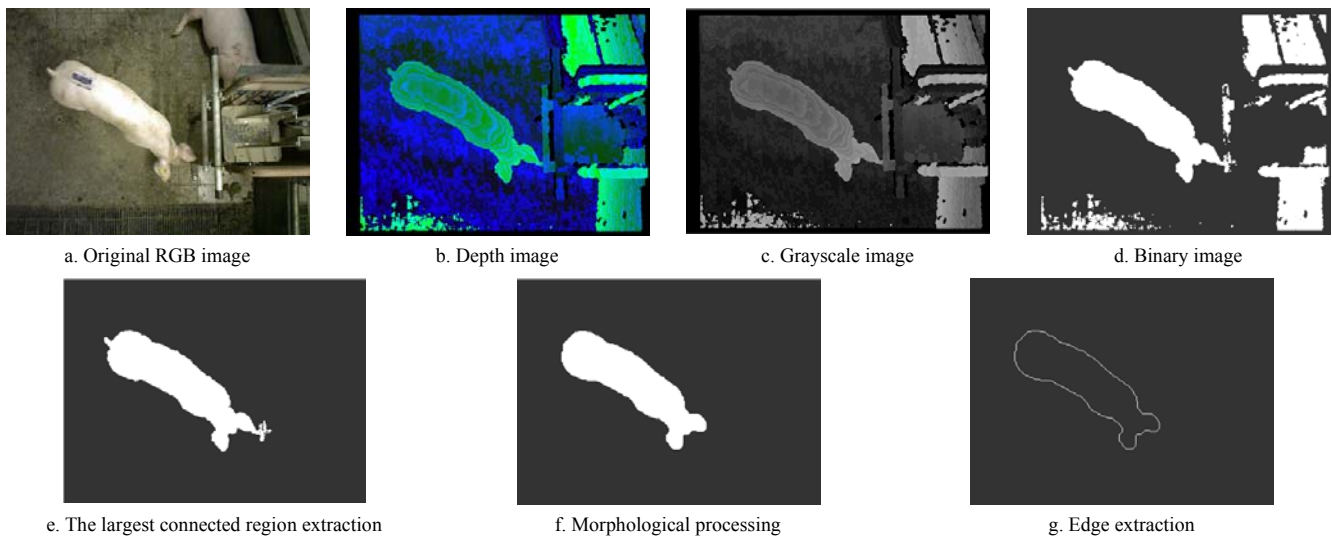


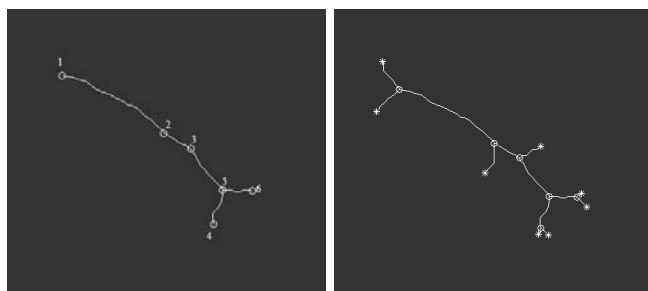
Figure 3 Image pre-processing

2.4.2 Pig's backbone line extraction

The extraction of the 2D backbone line consists of four steps. Firstly, skeleton extraction, in which, a skeleton is extracted from a pig's body contour. Secondly, a skeleton reduction is carried out, in which, branches with end points are removed from the skeleton. Thirdly, two binary trees are constructed for skeleton branch points. Finally, skeleton segments choice, in which, the skeleton branches that needed to be reserved is selected based on the branch points binary tree and Delaunay triangulated network.

(1) Skeleton extraction

An iterative thinning algorithm^[23] is used to extract the skeleton from a pig's body contour. The resulting skeleton of the pig's body contour in Figure 3g is shown in Figure 4a.



a. Skeleton extracted from the pig contour in Figure 3g
b. Reduction operation result of the skeleton in Figure 4a

Figure 4 Skeleton extraction and reduction

(2) Skeleton reduction

Points in a skeleton, as shown in Figure 4a, are divided into 3 categories: end points, branch points, and general points. The first and second ones are represented with star and circle points in Figure 4a, respectively. All other points in a skeleton, except for end points and branch points, are general points. A skeleton branch, started and ended with an end point or branch point, consists of points of the three categories mentioned above. A skeleton is reduced by removing branches with end points. The resulting skeleton of Figure 4a after the skeleton reduction operation is shown in Figure 4b, in which, all branches are started and ended with a branch point.

(3) Branch points binary tree construction

The two endpoints, denoted by sta_p and end_p respectively, of the longest branch in a reduced skeleton are extracted after the step 2.4.2.2. Two binary trees, rooted by sta_p and end_p , are constructed according to the neighbour relationship among branch points. Trees for branch points going to the direction of pig head and tail are denoted by T_h and T_t , respectively. Binary trees of the reduced skeleton branch points in Figures 4b, 5d and 5e are shown in Figures 5a-5c, respectively.

(4) Skeleton branches choice

A backbone line is part of the corresponding skeleton. It has the following character: except for the starting point and the finishing point, which has only one neighbor point, every other point in a backbone line has only two neighbor points. The

starting point and the finishing point, denoted by *backbone_start* and *backbone_end*, respectively, of a backbone line are chosen

based on the T_h , T_t , and the Delaunay triangulated network of the corresponding pig body contour.

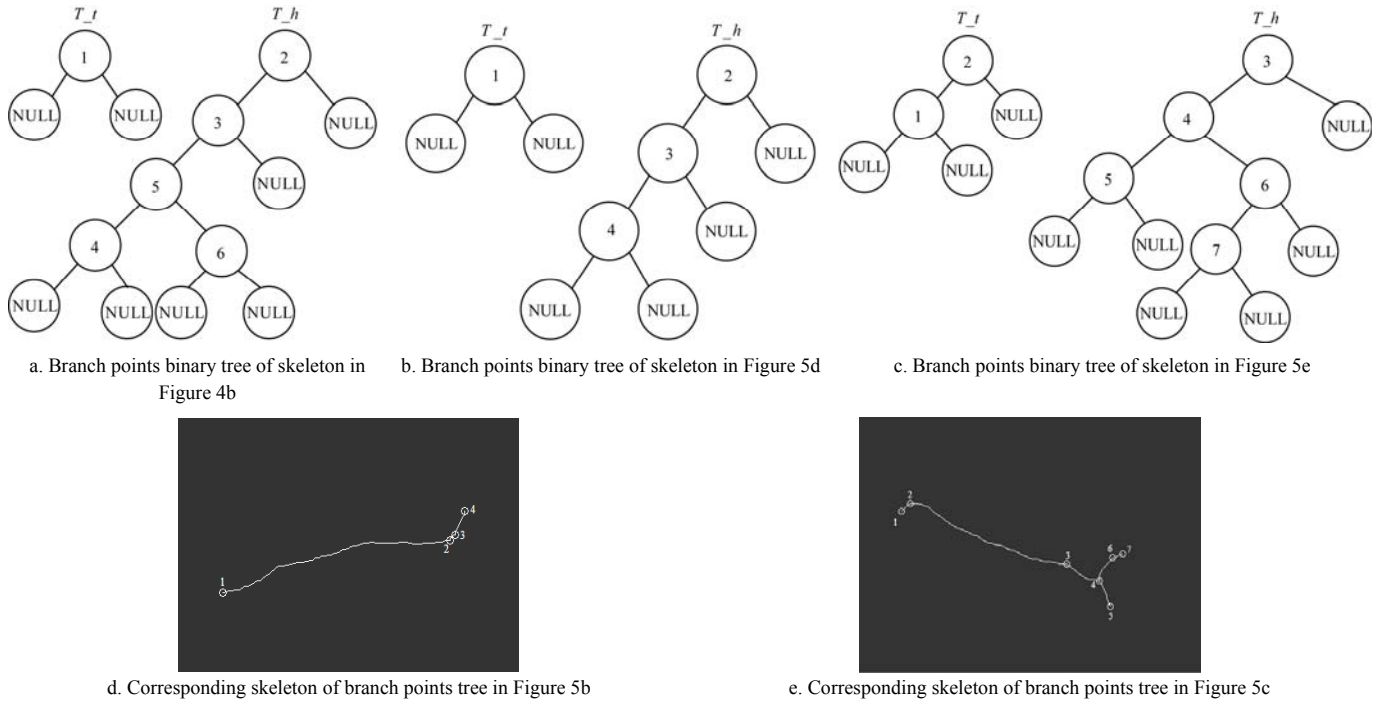


Figure 5 Binary trees of skeleton branch points

For most of T_h s, ear contours of the corresponding pig images are complete and symmetric. A branch point with three skeleton branches will appear in neck part. As the tree node number 5 in Figure 5a and tree node number 4 in Figure 5c, both of which have two children nodes. For this kind of T_h s, all branch points corresponding to tree nodes from the root to the node with two children are reserved. The branch point corresponding to the tree node with two children is set as the *backbone_start*. However, there are some other pig images, the ears contours of which are asymmetric. No branch point with three skeleton branches appears in these images. For example, tree node number 3 in Figure 5b has only one child. For this kind of T_h s, the leaf node (the children nodes are both NULL) is set as the *backbone_start*. *Backbone_start* is acquired from a T_h by using pseudo code 1.

Pseudo code 1

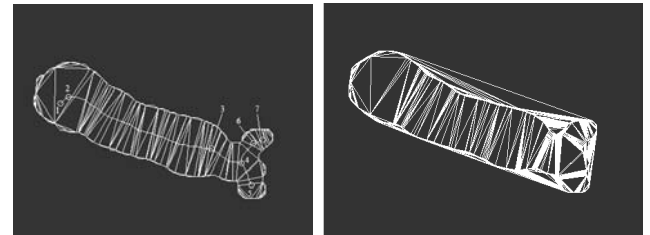
```
temp1=root_T_h;
while (!(temp1.left==null && temp1.right==null)) {
    if (temp1.left!=null && temp1.left!=null)
        break;
    else if (temp1.left!=null) {
        temp2=temp1.left;    temp1=temp2;
    }
    else if (temp1.right!=null) {
        temp2=temp1.right;    temp1=temp2;
    }
}
backbone_start=temp1;
```

where, $root_T_h$ is the root of the T_h .

All branch points in a T_t have only one child node after the operation of skeleton reduction. However, it does not mean that all branch points in the T_t should be reserved. Actually, there exist some skeleton branches, such as that located between branch point numbers 1 and 2 in Figure 5e, deviate from pig's backbone line greatly. These branches, which could bring false feature points, should be removed.

The Delaunay triangulated network is introduced to remove branches which deviate from pig's backbone line greatly. The spatial location relationship between the skeleton in Figure 5e and the corresponding Delaunay triangulated network is shown in

Figure 6a. Triangles in Figure 6a are a subset of triangles in Figure 6b, in which, triangles with an area less than ten pixels and triangles outside a pig contour are removed.



a. Spatial location relationship between skeleton in Figure 5e and the corresponding triangulated network

b. Original triangulated network of a pig contour

Figure 6 Triangulated network of the pig contour shown in Figure 3g

Segments deviating from pig's backbone line greatly are removed and the *backbone_end* is then obtained by processing a T_t with pseudo code 2.

Pseudo code 2

```
temp1=root_T_t;
while (!(temp1.left==NULL && temp1.right==NULL)) {
    choose the maximum area triangle from those located between pig center of gravity and pig tail;
    extract intersections of backbone line and the maximum area triangle;
    if (number of intersections==1) {
        temp1=intersection;    break;
    }
    else if (number of intersections==2) {
        temp1=the intersection whose distance to backbone_start is smaller;
        break;
    }
    else {
        if (temp1.left!=NULL)    Temp1=temp1.left;
        else temp1=temp1.right;
    }
}
backbone_end=temp1;
```

where, $root_T_t$ is the root of the T_t .

Pixel points located between *backbone_start* and *backbone_end* in a backbone line are stored in an array named

points_backbone. The extracted backbone line for the skeleton in Figures 4b, 5d, and 5e are shown in Figures 7a-7c, respectively.



a. Backbone line of the skeleton in Figure 4b



b. Backbone line of the skeleton in Figure 5d



c. Backbone line of the skeleton in Figure 5e

Figure 7 Backbone line extraction

2.4.3 Feature points extraction for pig contour

Based on the backbone line extracted in section 2.4.2, lengths variation of line segments which are perpendicular to a backbone line are used to extract feature points on a pig contour. It can be achieved by the following steps. Firstly, a curve, denoted by *cur_fit_backbone*, is fitted for a backbone line. Secondly, line segments which are perpendicular to *cur_fit_backbone* are extracted. Finally, lengths of perpendicular line segments are calculated and feature points are extracted based on the lengths variation of the perpendicular line segments.

(1) Curve fitting for backbone line

Firstly, a curve is fitted by pixel points in a *point_backbone* which is acquired in section 2.4.2. Secondly, the neighbour pixel point of *backbone_end* in a backbone line, denoted by *backbone_end_nei*, is extracted. The intersection, denoted by *inter_backbone_contour*, of pig's buttock contour and the tangent

of the backbone line's fitting curve in point *backbone_end_nei* is extracted. Then, *inter_backbone_contour* is added into *point_backbone*. Finally, *cur_fit_backbone* is fitted by all points in *point_backbone*. The *cur_fit_backbones* of the backbone lines in Figures 7a-7c are shown in Figures 8a-8c, respectively. Where, red smooth lines are the *cur_fit_backbones*, and thick white lines inside pig contours are backbone lines. White circle points in pig's buttock contours are *inter_backbone_contours*.

(2) Perpendicular line segments extraction

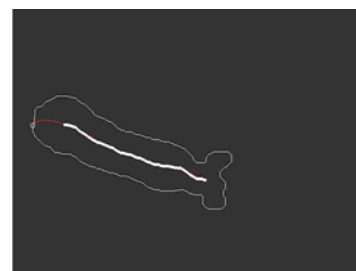
Intersections of a pig body contour and lines which are perpendicular to the corresponding *cur_fit_backbone* are extracted, as shown in Figures 9a-9c. Where, blue lines are perpendicular to each *cur_fit_backbone*, which is shown with a red smooth line inside each pig contour. Red points on each pig's contour are the extracted intersections, based on which, the length of each perpendicular line segment can be calculated.



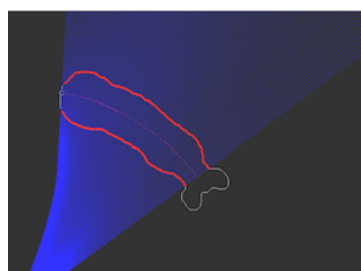
a. From Figure 7a



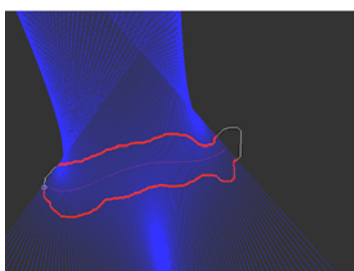
b. From Figure 7b



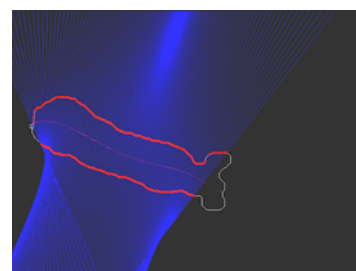
c. From Figure 7c

Figure 8 The *cur_fit_backbone* of the backbone line in Figure 7

a. From Figure 8a



b. From Figure 8b



c. From Figure 8c

Figure 9 Lines perpendicular to the *cur_fit_backbone* of the backbone line in Figure 8

(3) Feature points extraction

Starting with the line passing through the point *inter_backbone_contour*, the length of each perpendicular line segment is calculated one by one. For each perpendicular line in Figures 9a-9c, lengths variation of perpendicular line segments are shown in Figures 10a-10c, respectively, with solid lines. A polynomial curve, as shown in Figures 10a-10c with dashed line, is fitted for each solid line. Extract the first three local maximum (denoted by *loc_max_fit*) and minimum (denoted by *loc_min_fit*) points for each polynomial curve. *Loc_max_fits* and *loc_min_fits* are shown in Figures 10a-10c with hollow triangle points and

hollow circle points, respectively.

In ten points radius around each *loc_max_fit* and *loc_min_fit*, three local maximum points and minimum points on the original lengths variation curve, shown with solid lines in Figures 10a-10c, are extracted. Local maximum (denoted by *loc_max_orilen*) and minimum (denoted by *loc_min_orilen*) points on the original lengths variation curve are shown in Figures 10a-10c with star points and plus points, respectively. According to the *loc_max_orilens* and *loc_min_orilens*, twelve points on a pig contour are extracted and shown in Figures 10d-10f. Where, points labelled A to J are corresponding to feature points with the

same number in Figure 1b. Feature points labelled K to N will be acquired based on the points labelled A to J and K' to L' in Figure 10.

Feature point M is extracted by the following steps.

Step 1, calculate the area (denoted by S) of the shape enclosed by the perpendicular line segment AB (refer to Figure 10) and pig buttock contour.

Step 2, starting with point A , each pixel point (denoted by P) in pig buttock contour is extracted sequentially in the counterclockwise direction. Connect the center point of line segment AB (denoted by P_c) and P , and the area of the shape enclosed by segments PP_c , AP_c and pig buttock contour segment AP is calculated, which is denoted by S' . Repeat step 2 until $S/2 - S' < \tau$. Where, τ is a threshold, which is set to be 3 in BSDPE.

Step 3, each pixel point (denoted by M') in a five pixel points radius around P is extracted sequentially in the counterclockwise direction. For each M' , the distance (denoted by $dist_{M'_Pc}$) between M' and P_c is calculated. Point M' with the largest $dist_{M'_Pc}$ is chosen as the feature point M .

Feature point M for each pig contour shown in Figures 10a-10c are shown in Figures 11a-11c with yellow triangle points, respectively. Each point is labelled with a character M .

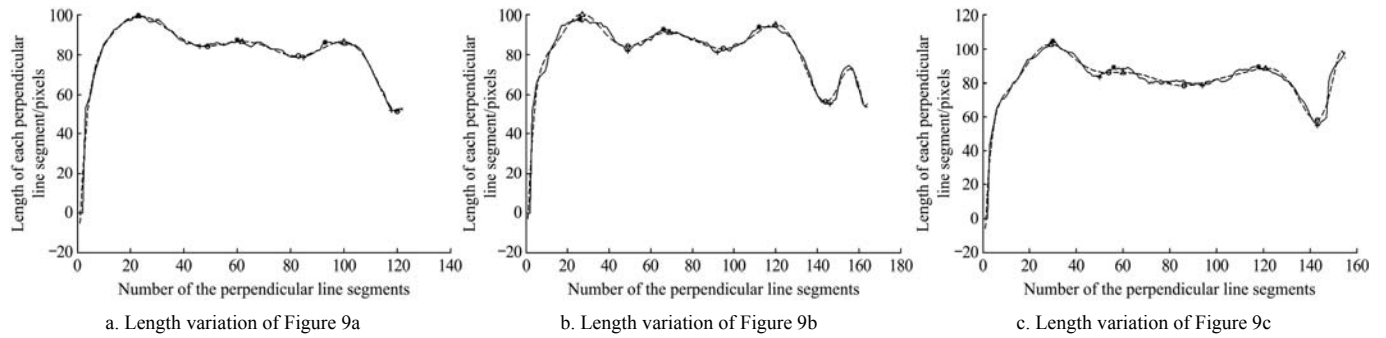
Feature points K to N are extracted by the following steps.

Step 1, direct least square method^[24-25] is adopted to fit an ellipse based on pixel points in the shorter contour segments IK' and JL' (refer to Figure 10). The fitted ellipse (denoted by E_{fit}) of each pig contour shown in Figures 10a-10c are shown in Figure 11a to Figure 11c, respectively.

Step 2, intersections of an E_{fit} and the corresponding pig contour are extracted. The intersection which is nearest to K' is selected to be feature point K . The intersection which is nearest to L' is selected to be feature point L .

Step 3, the shorter arcs section of E_{fit} ended by feature points K and L are extracted, which is denoted by KL_{min} . The intersection of KL_{min} and the $cur_fit_backbone$ is selected as the feature point N .

The extracted feature points K to N for Figures 10d-10f are shown in Figures 11a-11c, with yellow triangle points.



a. Length variation of Figure 9a

b. Length variation of Figure 9b

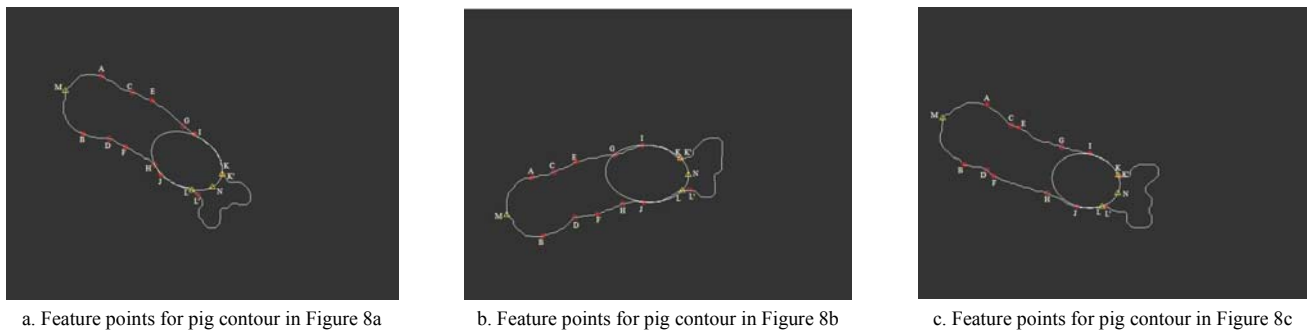
c. Length variation of Figure 9c

d. Feature points extracted from Figure 10a

e. Feature points extracted from Figure 10b

f. Feature points extracted from Figure 10c

Figure 10 Length variations of the perpendicular line segments in Figure 9 and twelve temporary feature points extracted based on the variation curves



a. Feature points for pig contour in Figure 8a

b. Feature points for pig contour in Figure 8b

c. Feature points for pig contour in Figure 8c

Figure 11 Feature points A to N for pig contour in Figure 8

2.4.4 Body surface dimension parameters calculation

Five features are need to be extracted, among which, four length features ($L1$ to $L4$) and one area feature ($A4$).

(1) Length features calculation

$L1$ to $L3$ is assigned the value of the length of line segment IJ ,

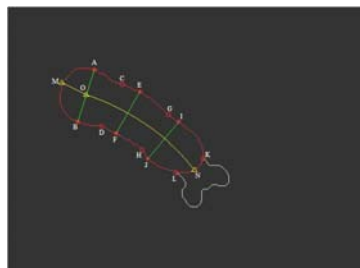
EF , and AB . Line segments AB , EF , and IJ are shown in Figure 12 with green lines.

For $L4$, the intersection of the $cur_fit_backbone$ with line segment AB is extracted, which is shown in Figure 12 with yellow triangle and labelled by O . Then, points M and O are connected

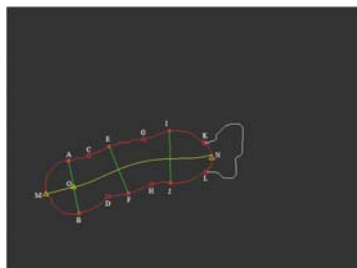
and the length of the line segment MO , denoted by len_{MO} , is calculated. Finally, calculate the length of the $cur_fit_backbone$ segment between points N and O , which is denoted by len_{curve_NO} . The sum of len_{MO} and len_{curve_NO} is assigned to $L4$.

(2) Area features calculation

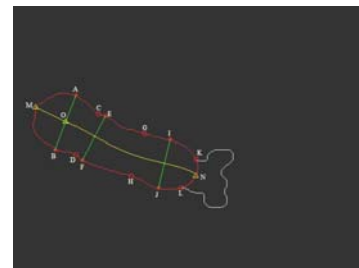
$A1$, $A2$, and $A3$ are calculated by using convex hull^[26] firstly in



a. Line segments for pig contour in Figure 8a



b. Line segments for pig contour in Figure 8b



c. Line segments for pig contour in Figure 8c

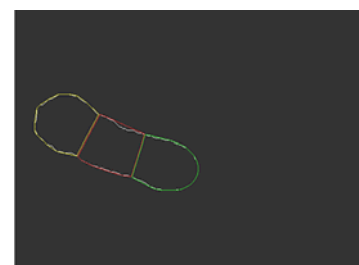
Figure 12 Line segments corresponding to $L1$ to $L4$ for pig contour in Figure 8



a. Convex hulls for pig contour in Figure 8a



b. Convex hulls for pig contour in Figure 8b



c. Convex hulls for pig contour in Figure 8c

Figure 13 Convex hulls for $A1$ to $A3$ of pig contour in Figure 8

Similarly, each convex hull for $A2$, denoted by $conhull_A2$ and shown in Figure 13a to Figure 13c with red line, is constructed by line segments CD and GH , pig body contour sections CEG and DFH . Each convex hull for $A3$, denoted by $conhull_A3$ and shown in Figure 13a to Figure 13c with yellow line, is constructed by line segment CD , pig body contour sections CMD . The area of $conhull_A2$ and $conhull_A3$ are calculated and assigned to $A2$ and $A3$, respectively. Finally, the sum of $A1$, $A2$, and $A3$ is assigned to $A4$. The five features of the three pig body surfaces shown in Figure 8 are shown in Table 1.

Table 1 Five dimension parameters (pixels) of the three pig body surfaces

Pig No.	$L1$	$L2$	$L3$	$L4$	$A4$
1	86.55	87.55	99.6	289.58	23516
2	94.04	92.8	97.72	309.47	25935
3	89.46	89.17	104.8	314.23	25890

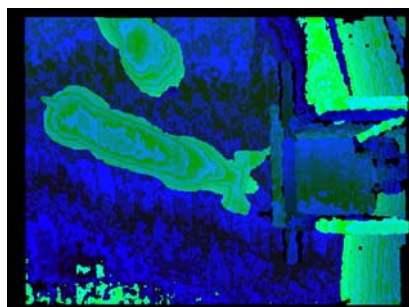
this part, and then $A4$ is assigned to the sum of $A1$, $A2$, and $A3$. For $A1$, a convex hull is constructed by the line segment GH , pig body contour sections GIK , HJL , and the ellipse section KNL . The convex hull for $A1$ (denoted by $conhull_A1$) of each pig contour shown in Figures 8a-8c are shown in Figures 13a-3c with green line, respectively. Then the area of $conhull_A1$ is calculated and assigned to $A1$.

3 Results and discussion

3.1 Algorithm testing

150 top-view depth pig images are selected randomly from the pig image database, which was collected by the camera system described in section 2. Because adhesive pigs segmentation is not taken into account in the proposed algorithm, images with adhesive pigs are removed. The remaining 126 images are processed and the body surface dimension parameters ($L1$ to $L4$ and $A4$ shown in Figure 1) are measured automatically, by using IMIX and BSDPE, respectively. Using the pig body surface dimension results, extracted by manual labelling tool, as the gold standard, the parameters accuracy of IMIX and BSDPE are compared.

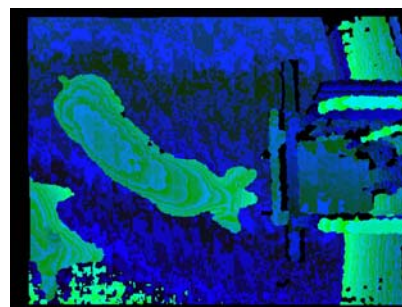
With three of the 126 images (Figure 14), for example, pig body surface dimension parameters results comparison between different methods is shown in Table 2. Where, length parameters (Li , $i=1$ to 4) and area parameter ($A4$) differences between IMIX or BSDPE and manual labelling tool are denoted by ΔLi ($i=1$ to 4) and $\Delta A4$.



a. Pig with a nearly straight body posture



b. Pig with a slightly curving body posture



c. Pig with an obvious curving body posture

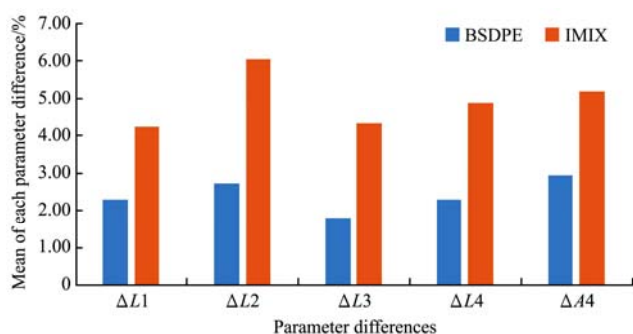
Figure 14 Images for parameters accuracy comparison

Table 2 Pig body surface dimension parameters results comparison between different methods

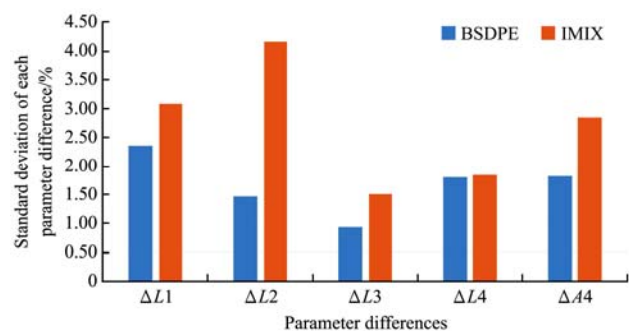
Image ID		$\Delta L1$	$\Delta L2$	$\Delta L3$	$\Delta L4$	$\Delta A4$
1	IMIX	2.57%	1.62%	2.22%	3.48%	4.17%
	BSDPE	1.11%	2.83%	1.69%	2.74%	1.35%
2	IMIX	3.24%	6.81%	2.21%	5.63%	5.51%
	BSDPE	2.16%	1.74%	4.25%	1.94%	1.98%
3	IMIX	6.97%	1.62%	1.70%	6.65%	6.23%
	BSDPE	2.50%	0.07%	1.37%	3.84%	2.57%

For all the 126 images, average accuracy comparison of each parameter obtained by BSDPE and IMIX is shown in Figure 15.

Where, ΔLi ($i=1$ to 4) and $\Delta A4$ have the same meaning with those in Table 2. The data presented in Figure 15 indicate that the mean and SE of parameters differences of BSDPE are lower, which means that BSDPE can extract pig body surface dimension parameters with a higher accuracy and reliability than IMIX.



a. Comparison of the mean of each parameter difference



b. Comparison of the standard deviation (SE) of each parameter difference

Figure 15 Comparison of length and area parameters accuracy

3.2 Discussion

Pig body surface dimension parameters can be used to estimate pig live weight and carcass traits. However, pigs' postures are diverse, which makes parameter extraction based on image processing difficult. In this study, an algorithm, named by BSDPE, is proposed to extract length parameters ($L1$ to $L4$) and an area parameter ($A4$) from top-view pig depth images automatically. By using manual labelling results as a gold standard, the average accuracy of length and area parameters of BSDPE are found to be 97.71% ($SE=1.64\%$) and 97.06% ($SE=1.82\%$), respectively. These results are better than those of IMIX, which are found to be 95.12% ($SE=2.66\%$) and 94.82% ($SE=2.85\%$). Moreover, t -test results show that the p -value of length and area parameters accuracy between BSDPE and IMIX are 6.27×10^{-8} ($p < 0.05$) and 0.0358 ($p < 0.05$), respectively. It means that there's a significant difference between the two algorithms in parameters extraction accuracies.

Parameters accuracy improvement is due to the following two aspects. Firstly, backbone line extracted in BSDPE can follow

pig's backbone line accurately, which in turn brings more accurate feature points location in pig body contour. Secondly, the curve used to cut pig head and neck is acquired by an ellipse which is fitted by pig shoulder contour points. The variation of pig's body posture has very little impact on the shape and size of the fitted ellipse, which brings a more reasonable curve for pig head and neck removing.

In terms of a further accuracy improvement of pig body surface area parameters, a better method for surface area calculation is worth studying. In BSDPE, area parameters are calculated by using convex hull. For a pig body which has no concave part (such as pig body in Figures 13a and 13b), convex hull will return accurate area results. However, concave part will exist, usually in a pig's trunk, when the pig stands with an obvious curving body posture, as shown in Figure 13c. A concave part will reduce area parameters accuracy calculated based on convex hull. Therefore, a better area calculation method which can deal with concave part in pig body surface is worth to study in the future.

In terms of practical application of BSDPE, the following two aspects should be considered in the future. Firstly, BSDPE should be improved to extract dimension parameters for images with adhesive pigs. It can be achieved by combining BSDPE with adhesive pigs segmentation method^[25, 27-28]. Secondly, pig height should be taken into account to acquire actual pig body surface dimension parameters. Images in this study were captured by top-view cameras. Therefore, pig height will influence its body surface dimension in images. That is, for pigs with the same actual body surface dimension and different height, body surface dimension extracted by BSDPE will be different. This definitely influences the accuracy of the estimation results of live weight and carcass traits. Thus, with the height information obtained from depth images captured by KINECT cameras, body surface dimension parameters extraction with height compensation should be considered in future work.

4 Conclusions

An algorithm is developed to extract pig body surface dimension parameters from depth images. The algorithm is based upon pig body skeleton, the Delaunay triangulated network, and ellipse fitting. Firstly, pig's backbone line is extracted by using skeleton branch points binary tree and the Delaunay triangulated network. Secondly, lengths of line segments defined by intersections of pig contour and lines perpendicular to the backbone line are calculated. Feature points on a pig contour are extracted by the lengths variation of line segments which are perpendicular to the backbone line. Thirdly, the head and neck of a pig is removed by an ellipse, which is fitted by the pig's shoulder contour sections. Finally, five pig body surface dimension parameters are calculated based on the feature points and pig contour without head and neck.

The proposed algorithm is implemented in Matlab[®] (R2012b) and applied to 126 top-view depth pig images. By using manual labelling results as a gold standard, the accuracy of length and area parameters extracted by BSDPE are 97.71% ($SE=1.64\%$) and 97.06% ($SE=1.82\%$), respectively. The accuracies are better than those of IMIX, which are 95.12% ($SE=2.66\%$) and 94.82% ($SE=2.85\%$), respectively. The improvement of pig body surface dimension parameters accuracy can improve the accuracy of pig live weight and carcass traits estimation, which is essential for breeders to adjust management regime.

Acknowledgments

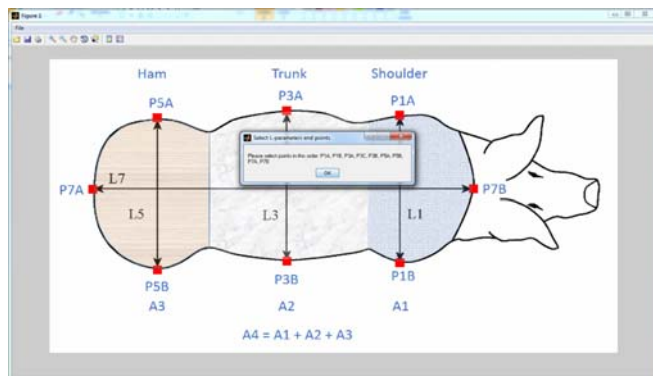
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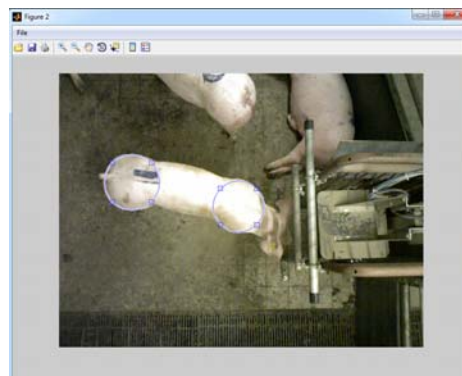
Appendix 1

The manual labelling software is named by “PigAreaLabelling.exe”. The main steps of the manual labelling tool are described below.

Step 1, run “PigAreaLabelling.exe”, a window appears showing the template image and asking to select the points in a certain order, as shown in Figure 16a.



a. Illustration of the order of points selection



b. Ellipses in ham and shoulder



c. End point selection for each line segment



d. Border definition of pig body

20140326-192928_01-0000-depth.txt				
1	Point	X	Y	
2	P1A	328	188	
3	P1B	302	274	
4	P3A	224	161	
5	P3B	212	246	
6	P5A	133	142	
7	P5B	112	239	
8	P7A	80	182	
9	P7B	364	255	
10				
11	AreaA4	23643	squared pixels	

e. Manual labelling results

Figure 16 Screenshots of each main step of the manual labelling tool

Step 2, the operator is asked to move and resize two ellipses so that they are inscribed to the ham and shoulder, respectively, as shown in Figure 16b.

Step 3, end points of line segments corresponding to $P1AP1B$, $P3AP3B$, and $P5AP5B$ in Figure 16a, are chosen, as shown in Figure 16c. The middle points of $P1AP1B$, $P3AP3B$, and $P5AP5B$ are denoted by $P1C$, $P3C$, and $P5C$, respectively.

Step 4, the operator is asked to draw the border of $A4$ (pig body area), as shown in Figure 16d.

Step 5, manual labelling results are provided in a text file, as shown in Figure 16e. Coordinates of each point (defined as

shown in Figure 16a) are recorded in rows 2-9. $A4$ area is recorded in row 11. $L1$, $L2$, $L3$, $P1C$, $P3C$, and $P5C$ are calculated based on the coordinates shown in Figure 16e. $L7$ is the summation of the lengths of the following line segments: $P7AP5C$, $P5CP3C$, $P3CP1C$, and $P1CP7B$.

[References]

- [1] Jørgen K. Estimation of pig weight using a Microsoft Kinect prototype imaging system. *Computers and Electronics in Agriculture*, 2014; 109(11): 32–35.
- [2] Schofield C P, Marchant J A, White R P, Brand N, Wilson M.

- Monitoring pig growth using a prototype imaging system. *Journal of Agricultural Engineering Research*, 1999; 72(3): 205–210.
- [3] Wang Y S, Yang W, Walker L T, Rababah T M. Enhancing the accuracy of area extraction in machine vision-based pig weighing through edge detection. *International Journal of Agricultural and Biological Engineering*, 2008; 1(1): 37–42.
- [4] Brown C. Who matters? The changing market: Perspective from multiple retailers. In the appliance of pig science. *British Society of Animal Science*, 2004; 31: 19–22.
- [5] Shi C, Teng G H, Li Z. An approach of pig weight estimation using binocular stereo system based on LabVIEW. *Computers and Electronics in Agriculture*, 2016; 129(1): 37–43.
- [6] Doeschl A B, Green D M, Whittemore C T, Schofield C P, Fisher A V, Knap P W. The relationship between the body shape of living pigs and their carcass morphology and composition. *Animal Science*, 2004; 79: 73–83.
- [7] White R P, Schofield C P, Green D M, Parsons D J, Whittemore C T. The effectiveness of a visual image analysis (VIA) system for monitoring the performance of growing/finishing pigs. *Animal Science*, 2004; 78(3): 409–418.
- [8] Collewet G, Bogner P, Allen P, Busk H, Dobrowolski A, Olsen E, et al. Determination of the lean meat percentage of pig carcasses using magnetic resonance imaging. *Meat Science*, 2005; 70(4): 563–572.
- [9] Kusec G, Baulain U, Kallweit E, Glodek P. Influence of MHS genotype and feeding regime on allometric and temporal growth of pigs assessed by magnetic resonance imaging. *Livestock Science*, 2007; 110: 89–100.
- [10] Schinkel A P, Einstein M E, Jungst S, Booher C, Newman S. Evaluation of different mixed model nonlinear functions to describe the body weight growth of pigs of different sire and dam lines. *Prof. Anim. Sci.*, 2009; 25: 307–324.
- [11] Kashiha M, Bahr C, Ott S, Moons C P H, Niewold T A, Ödberg F O, et al. Automatic weight estimation of individual pigs using image analysis. *Computers and Electronics in Agriculture*, 2014; 107: 38–44.
- [12] Marchant J A, Schofield C P, White R P. Pig growth and conformation monitoring using image analysis. *J. Anim. Sci.*, 1999; 68: 141–150.
- [13] Fisher A V, Green D M, Whittemore C T, Wood J D, Schofield C P. Growth of carcass components and its relation with conformation in pigs of three types. *Meat Sci.*, 2003; 65: 639–650.
- [14] Green D M, Brotherstone S, Schofield C P. Food intake and live growth performance of pigs measured automatically and continuously from 25 to 115 kg live weight. *J. Sci. Food Agric.*, 2003; 83: 1150–1155.
- [15] Brandl N, Jørgensen E. Determination of live weight of pigs from dimensions measured using image analysis. *Computers and Electronics in Agriculture*, 1996; 15: 57–72.
- [16] Whittemore C T, Schofield C P. A case for size and shape scaling for understanding nutrient use in breeding sows and growing pigs. *Livestock Prod. Sci.*, 2000; 65: 203–208.
- [17] Banhazi T M, Tschärke M, Ferdous W M, Saunders C, Lee S H. Using image analysis and statistical modelling to achieve improved pig weight predictions. *Biennial Conference of the Australian Society for Engineering in Agriculture (SEAg)*, 2009; pp.13–16.
- [18] Apirachai W, Banchar A, Supachai P. An approach based on digital image analysis to estimate the live weights of pigs in farm environments. *Computers and Electronics in Agriculture*, 2015; 115(7): 26–33.
- [19] Tasdemir S, Urkmez A, Inal S. Determination of body measurements on the Holstein cows using digital image analysis and estimation of live weight with regression analysis. *Computers and Electronics in Agriculture*, 2011; 76: 189–197.
- [20] Mollah Md B R, Hasan Md A, Salam Md A, Ali Md A. Digital image analysis to estimate the live weight of broiler. *Computers and Electronics in Agriculture*, 2010; 72(1): 48–52.
- [21] Liu T H, Teng G H, Fu W S, Li Z. Extraction algorithms and applications of pig body size measurement points based on computer vision. *Transactions of the CSAE*, 2013; 29(2): 161–168. (in Chinese)
- [22] Otsu N. A threshold selection method from gray-level histograms. *IEEE Transactions on Systems Man and Cybernetics*, 1979; 9(1): 62–66.
- [23] Haralick R M, Shapiro L G. *Computer and Robot Vision*, Addison-Wesley Longman Publishing Co., Inc., Boston, MA, 1992.
- [24] Halif R, Flusser J. Numerically stable direct least squares fitting of ellipses. *Proc. Sixth Int'l Conf. Computer Graphics and Visualization*, 1998; pp.125–132.
- [25] Lu M Z, Xiong Y J, Li K Q, Liu L S, Yan L, Ding Y Q, et al. An automatic splitting method for the adhesive piglets' gray scale image based on the ellipse shape feature. *Computers and Electronics in Agriculture*, 2016; 120(1): 53–62.
- [26] Barber C B, Dobkin D P, Huhdanpaa H T. The Quickhull Algorithm for Convex Hulls. *ACM Trans. on Mathematical Software*, 1996; 22(4), 469–483.
- [27] Kashiha M, Bahr C, Haredasht S A, Ott S, Moons C P H, Niewold T A, et al. The automatic monitoring of pigs water use by cameras. *Computers and Electronics in Agriculture*, 2013; 90: 164–169.
- [28] Nasirahmadi A, Hensel O, Edwards S A, Sturm B. Automatic detection of mounting behaviors among pigs using image analysis. *Computers and Electronics in Agriculture*, 2016; 124: 295–302.