Computers and Electronics in Agriculture 138 (2017) 60–68

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

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

Original papers

LSSA_CAU: An interactive 3d point clouds analysis software for body measurement of livestock with similar forms of cows or pigs

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ARTICLE INFO

Article history:
Received 7 February 2017
Received in revised form 20 April 2017
Accepted 21 April 2017

Keywords:
Point clouds
Depth camera
Body measurement
Livestock

ABSTRACT

As increasing number of studies for shape measurement purposes in livestock farming by using consumer depth cameras, many software have been developed in order to measure livestock conformation. However, many of these softwares were designed only for specific livestock or body part of specific livestock with very limited body measurements. To be more flexible and general compared to the current software provided in the literature, an interactive software LSSA_CAU is developed to estimate body measurements of livestock based on 3d point clouds data. Livestock with similar forms of cows or pigs and standing with her head forward is assumed for designing algorithm used in LSSA_CAU. This software provides a set of tools for loading, rendering, segmenting, pose normalizing, measuring point clouds data of whole body surface of livestock in a semiautomatic manner. In order to validate the software, both synthetic and real world point clouds data of livestock were processed by using the LSSA_CAU. Our experiments show that the proposed software generalizes well across livestock species and supports customized body measurements. An updated LSSA_CAU version can be downloaded freely from https://github.com/LiveStockShapeAnalysis to livestock industry and research.

1. Introduction

The possibility of frequently monitoring animals body condition in a quantitative way is of help in order to allow early recognition of health anomalies and accordingly reduce occurrence of problems connected to infertility, lameness or other diseases (Roche et al., 2009). In the case of young cattle, the first months are fundamental since animal growth can be reduced by occurrence of different diseases or other stressing factors. Similarly in the case of adult cows or other livestock species, the measurement of body condition and development is relevant in order to monitor their welfare, and thus keep high productivity levels (Azzaro et al., 2011; Doeschl et al., 2004; Topal and Macit, 2004). In the last fifty years, live body weight or body measurements have been the most straightforward way to measure individual animals body development. However, manual body measurement are time consuming and costly for farmers. On the other hand, high levels of stress can be induced by manual measurements, especially in the case of younger livestock. Additionally, such techniques may injure livestock farmers.

To overcome the limitations of conventional measurement system, machine vision has been used extensively as a non-intrusive approach for animal body measurement (Kuzuhara et al., 2015). Several researchers assessed the feasibility of utilizing video and digital images to determine body shape, condition, and weight in dairy cows (Tasdemir et al., 2011; Azzaro et al., 2011), pigs (Brandl and Jorgensen, 1996; Marchant et al., 1999; Wongsriworaphon et al., 2015), sheep (Yilmaz et al., 2013; Menesatti et al., 2014), horse (Pallottino et al., 2015), broilers (Mortensen et al., 2016) and fish (Saberioon et al., 2016). The use of imaging or vision systems to predict or measure livestock development has been presented in several papers during last 30 years. Vision systems based on visible light is often affected by variation in ambient lighting, and must be calibrated accordingly. Subtraction of background is often a difficult task due to differences in animal color, complex scene in flexible living conditions. To overcome these drawbacks of using a standard camera for assessing body shape, researchers have examined the use of other imaging system such as ultrasound (Duff et al., 2010) and thermal cameras (Halachmi et al., 2013). 2-D images only offer two dimensional projection of the animal. The lack of the third dimension in vision limits applications utilizing depth information (Stajnko et al., 2008). Photogrammetry stereo techniques have been introduced to measure farm animals in three dimensions (3-D). One such suc-

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http://dx.doi.org/10.1016/j.compag.2017.04.014
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cessful example is a stereo vision system with six 2-D cameras and three flash units used to capture the 3-D shapes of pigs (Wu et al., 2004). However, these photogrammetric systems are difficult to implement. Novel 3-D systems can solve the problems posed by conventional 2-D vision systems, including photogrammetry stereo techniques. As a result, there has been increasing demand for these techniques in livestock farming (Weber et al., 2014).

Recently, consumer depth sensor based on a structured infrared-light (IR) system, such as the Microsoft Kinect or the ASUS's Xtion Pro, provide 3D data at low cost and has opened new possibilities for acquiring information of livestock conformation (Guo et al., 2013; Kawasue et al., 2013; Viazzi et al., 2014). The feasibility of using 3D camera imaging to estimate (body condition scoring) BCS for cow had been addressed (Viazzi et al., 2014; Weber et al., 2014). Weber et al. implemented the software for recording 3-D images from TOF camera (SwissRan-ger SR4000, MesaImaging, Switzerland), taken several cuts along aligned pose of cow through a cow's surface in order to calculate traits that are meaningful to the surface's changes induced by varying body condition during lactation (Weber et al., 2014). But they only focused on the animals' rear part. A calibrated 3D reconstruction system for cattle using three Kinect sensors was introduced, the important traits for evaluating the shape and posture of the cow were estimated using the point cloud data (Kawasue et al., 2013). Based on commercial software Artec Studio 9.2, the capacity for using back posture measurements of dairy cows with Xtion Pro Live to predict BCS and body weight (BW) as well as milking traits such as MY, milk fat (MF), and milk protein (MP) concentrations was evaluated (Kuzuhara et al., 2015). The major difference of this study is that they manually measured geodesic distance on six selected body regions so as to obtain body condition measurements. As increasing number of studies for shape measurement purposes in livestock farming, many software have been developed in order to acquire 3D surface data of livestock (Kawasue et al., 2013; Weber et al., 2014; Guo et al., 2014), to measure livestock conformation (Weber et al., 2014) or to estimate the livestock weight (Wongsriworaphon et al., 2015; Yilmaz et al., 2013). However, many of these softwares were designed only for specific livestock or part of specific livestock body. The most of existing point clouds software for reverse engineering or survey service, such as Geomagic and VRMesh (List of programs for point cloud processing, 2014), are capable of measuring, however, if you are measuring livestock point clouds it will need complex user interaction to align, measure livestock.

In view of the above, the main objective of this study was to develop flexible and general software named LSSA_CAU for analysis of livestock 3d point clouds, in order to estimate morphometric traits or body measurements defined by user in commercially interesting livestock species: cows, pigs, other livestock with similar form with those two species such as horses; and to validate this software by analyzing both synthetic and real world livestock point clouds acquired by using multiple depth cameras system (Guo et al., 2014) which we designed before. The targeted users of the LSSA_CAU software are livestock breeders, livestock farmers. In addition, LSSA_CAU can be used to enable lecturers, students and researchers in the fields related with livestock to explore and illustrate the relationship between livestock morphometric traits with other kinds of traits.

2. Materials and methods

2.1. Livestock 3D data requirements

In order to design the algorithms and implement the software, we aim to make some assumptions about the input 3D data of software in this section. Livestock body measurements require the scanning of rather complex three-dimensional animals to incorporate them into our computer-aided processing. There are three types of techniques, existing in the literature so far, which are able to digitize livestock's surfaces, namely photogrammetric stereo imaging system (Wu et al., 2004; McFarlane et al., 2005), time of flight depth cameras (TOF) (Salau et al., 2014) and consumer depth cameras like Kinect (Kawasue et al., 2013). They all can easily produce a large amount of points lying on the livestock's surfaces. Such a point set representing the surface of livestock we call a point cloud. Thus, let's start from a point cloud denoted by $S = \{p_i\}$, each point p_i has color or not and no other information. Without loss of generality, we assume that the input point clouds S mainly consist of one livestock standing on a planar ground plane with possible parts of other livestock facilities. Additionally, we make the following two assumptions about the livestock to be measured.

(1) A livestock has similar forms of cows or pigs which have small head in relation to their body size, long body with four legs, shorter hair.
(2) A livestock stand on the horizontal ground plane with her head forward. That is to say, the skeleton of pig top view is almost a straight line.

The first assumption is a requirement of the livestock shape that restrict our software and algorithms within specified range of application. The second one is an assumption of the pose of livestock that simplifies the pose normalization in the subsequent section. So are the assumptions of the composition of the input point clouds S. Fig. 2 shows the example of qualified input point cloud acquired by using our prototype system (Fig. 1) for animal 3D reconstruction (Guo et al., 2014). Multi-view 3D acquisition is out of scope of this research paper and is not a trivial task. We recommend readers refer to our paper about 3D scanning of pig (Guo et al., 2014), another research about 3D scanning of cows (Kawasue et al., 2013) and general multi-view real time 3D acquisition technique (Shim et al., 2012). Note that we have to keep the other livestock away from the one we are going to measure in practice. Thus we can guarantee that the point clouds acquired comply with the assumption that S only contains one livestock. Meanwhile we manually choose the frames which meet our requirements, since the output of our scanning system is point clouds sequences.

Fig. 1. Our prototype system (Guo et al., 2014) used for acquiring point clouds in this research.

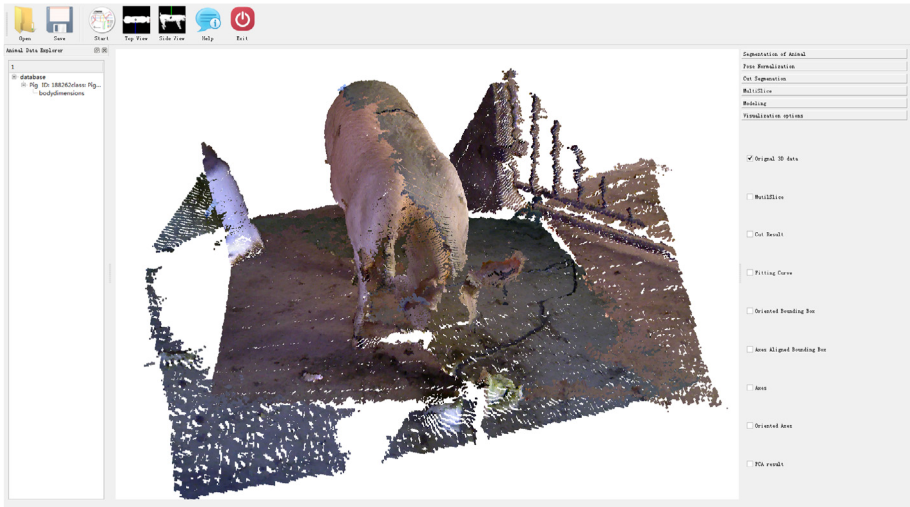


Fig. 2. One example of qualified input point clouds.

2.2. Segmentation and pose normalization approach

A full, rigorous description of the point cloud processing technical background of LSSA_CAU is given elsewhere (Rusu, 2011). Here, we outline in brief the processing pipeline of two critical step, which are sufficient to allow the work to be reproduced.

2.2.1. Automatic segmentation of livestock

Before we proceed to further processing, the segmentation of input point clouds into livestock and background is a necessary operation in the our workflow. To do so we firstly detect the ground plane based on RANSAC (Schnabel et al., 2007) as it follows. We begin by downsampling the input point clouds S using an octree with leaf size d_r. At most one point per leaf is retained and all subsequent steps are applied on the downsampled point clouds denoted by $D = \{p_i\}$. Where i is the point index. Typically, $2r$ is used as the leaf size, where r is the resolution of the point cloud defined as the average distance between neighboring points. The RANSAC paradigm extracts plane by randomly drawing three points from the point clouds D and constructing corresponding plane. The resulting candidate planes are tested against all points in D to determine how many of the points are well approximated by the candidate planes (called the score of the plane). After a given number of trials, the plane which approximates the most points is extracted and is defined as ground plane denoted by P_g. Typical values for the parameters of RANSAC are: 10,000 iterations and $\varepsilon = 3r$. Where ε is largest distance allowed between the inliers and plane. Fig. 3 shows a visualization of ground plane detection results on the data of Fig. 2.

Based on the ground plane detected, our algorithm removes ground plane from the D. Specifically, we remove all the inliers denoted by P_g^p. Inliers here are points with distance from the ground plane P_g less than $\varepsilon = 3r$. Once this operation has been performed, the different structures are no longer connected through the floor, so they could be clustered by labeling neighboring 3D points on the basis of their Euclidean distance. Thus, we cluster points of $D - P_g^p$ using region growing to obtain a set of clusters, as shown in Fig. 4.

$$C = \{C_1, \ldots, C_M\}$$

Each of these clusters is grown from a point p_i, an unclustered point, in $D - P_g^p$. A new point p_j is added to the cluster if it is the single nearest neighbor of a point p_m which is already in the cluster. In order to avoid the clusters formed due to clutter, clusters with less than a minimum number of points (500) are discarded. Then, the largest cluster in C, in terms of number of points, is denoted by C_*. According to the assumption in Section 2.1 that the input point clouds mainly consist of one livestock standing on a planar ground plane with possible parts of other livestock facilities, we can infer that the largest cluster C_* contains all points lying on the livestock. Fig. 5 shows a visualization of livestock segmentation results on the data of Fig. 2.

2.2.2. Semi-automatic pose normalization of livestock

3D reconstruction of livestock are generally given in arbitrary position and orientation in 3D-space. However, most of traits are measured along the body direction or its vertical direction when examining a livestock's conformation. Hence, in order to reduce the human operators involved using measurement software it is important to define a appropriate canonical coordinate system which is easy to measure most of traits for livestock. The aim of pose normalization is to match the livestock and the canonical coordinate system through a rigid 3D transformation. Considering the fact that most of traits are measured along the body direction, we define the body direction and its vertical direction as two of the principal axes of the livestock. As seen from Fig. 6, the canonical coordinate system for livestock uses the following axis definitions:

- The origin of canonical coordinate system is positioned at the centroids of livestock.
- The X-axis is defined by the anterior-posterior axis, while its positive direction is anterior.
- The Y-axis is defined by the dorsal-ventral axis, while its positive direction is dorsal.
- The Z-axis is defined by the medial-lateral axis, while its positive direction is lateral right.

Though many different pose normalization methods exist, the one that we will apply on this study is one of the best-known approach Principal Component Analysis (PCA) (Vranic et al., 2001). The PCA algorithm, based on the computation of 3D object moments, estimates the principal axes of a 3D object that are used to determine its three major orientation. The solution for estimating canonical coordinate system is therefore reduced to an analysis of the eigenvectors and eigenvalues of a covariance matrix created from the livestock point clouds C_*. More specifically, we assemble the covariance matrix **Cov** as follows:

Fig. 3. Visualization of ground plane detection results on the data of Fig. 2.

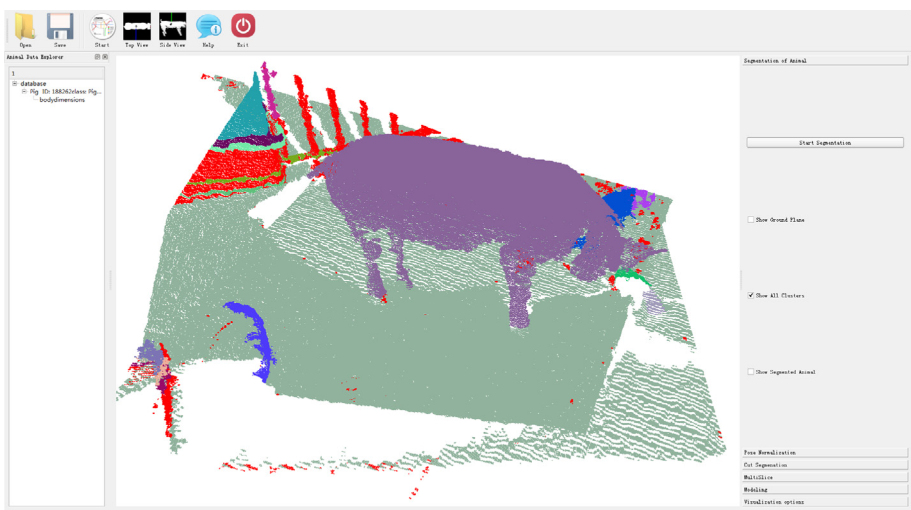


Fig. 4. Visualization of clustering points of $D - P_g^p$ using region growing results on the data of Fig. 2.

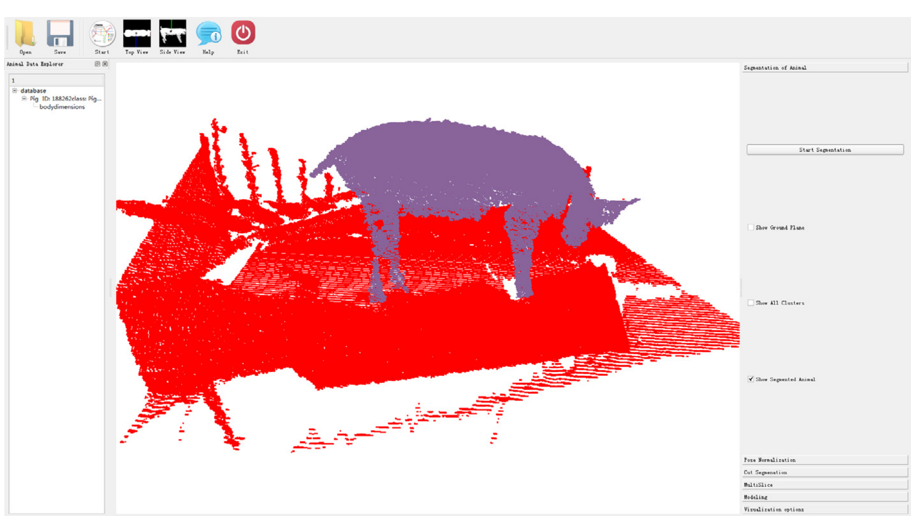


Fig. 5. Visualization of livestock segmentation results on the data of Fig. 2.

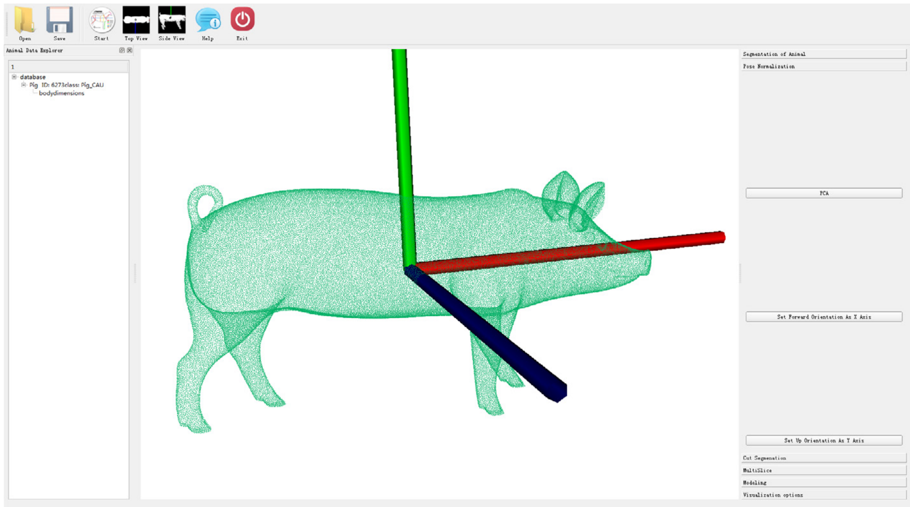


Fig. 6. The canonical coordinate system definition.

$$\mathbf{\bar{o}} = \frac{1}{N}\sum_{i=1}^{N}\vec{p_i},$$
$$\mathbf{Cov} = \frac{1}{N}\cdot\sum_{i=1}^{N}(\vec{p_i}-\mathbf{\bar{o}})(\vec{p_i}-\mathbf{\bar{o}})^T, \quad (1)$$
$$\mathbf{Cov}\cdot\vec{v_j} = \lambda_j\cdot\vec{v_j}, \quad j\in\{1,2,3\}$$

where N is the number of point in C_*, $\vec{p_i}$ is the vector representation of point $p_i \in C_*$, $\mathbf{\bar{o}}$ represents the 3D centroid of livestock point clouds C_*, λ_j is the j-th eigenvalue of the covariance matrix, and $\vec{v_j}$ the j-th eigenvector. Notice the eigenvectors are sorted by their eigenvalues largest to smallest – the first principle component (eigenvector) represents the most variance and the last component the least. Based on the observation that the direction along the livestock body points in the direction of the most variance, upright direction of livestock points in the direction of the least variance. Thus we can infer that X, Y, Z-axes are along $\vec{v}_1, \vec{v}_2, \vec{v}_3$ respectively. In general, because there is no mathematical way to solve for the sign of the $\vec{v_j}$, its orientation computed via Principal Component Analysis (PCA) is ambiguous, and not consistent with the positive directions of X, Y, Z-axes in canonical coordinate system. Therefore, we add a button onto the user interface to allow user to re-orient the $\vec{v_j}$ manually in software. After that, we estimate a 3D rigid transformation $\mathbf{T}$ between origin coordinate system and canonical coordinate system. Then the transformation estimated is applied on C_* so as to obtain the pose-normalized point clouds denoted by C_t. Fig. 7 shows a visualization of pose normalization result on the corresponding input point clouds data. Note that all subsequent steps for body measurement are applied on C_t.

2.3. Development of software for livestock body measurement

LSSA_CAU is a desktop application with graphical user interface (GUI). It is developed in C++. The cross-platform application framework Qt is used for GUI related tasks. The Point Cloud Library (PCL) (Rusu, 2011) is used for many of the supporting tasks, like point cloud loading, segmentation and visualization. LSSA_CAU semiautomatically processes the input point clouds individually. The critical stages of LSSA_CAU development with PCL and Qt are briefly discussed in the following sections.

2.3.1. Loading, segmentation and pose normalization for input point clouds

In order to load the input data, we design a class A that loads input point clouds from a file. A is derived from QObject to use Qt's signal/slot mechanisms, so are all subsequent classes. A contains one slot function that responsible for loading data by using loadPCDFile function from PCL, one signal for informing other classes the loading result. The supporting point clouds data file type is pcd. Additionally, note that the input point clouds data must satisfy the requirement in Section 2.1. Otherwise, the measurement results is undefined.

In order to implement the segmentation and pose normalization algorithm described in previous section, the class SACSegmentation from PCL is used for ground plane detection. The vector operations involved in our software are programmed by Eigen library (Rusu, 2011) which offers matrix/vector arithmetic operations either through overloads of common C++ arithmetic operators such as $+, -, *$, or through special methods such as dot product, cross product, etc. Class EuclideanClusterExtraction from PCL is used for labeling neighboring 3D points on the basis of their Euclidean distance involved with segmentation of livestock in Section 2.2. Additionally, Class MomentOfInertiaEstimation is used for computing three major axes of pose normalization. The other operations are implemented by ourselves.

2.3.2. Livestock body measurement

As we all know, each livestock species has its own anatomical and morphometric particularities. To make LSSA_CAU more versatile, We divide livestock body measurements into following 7 major categories in terms of number of anatomical points needed when measuring:

1. perpendicular distance from a point to ground plane, like height;
2. circumference of cross-section parallel to the y-z plane, like heart girth;
3. distance between two points along y axis, like chest width;
4. distance between two points along z axis, like body depth;
5. distance between two points along x axis, like body length;
6. distance between two points, customed measurement may useful;
7. angle defined by three points, like foot angle;

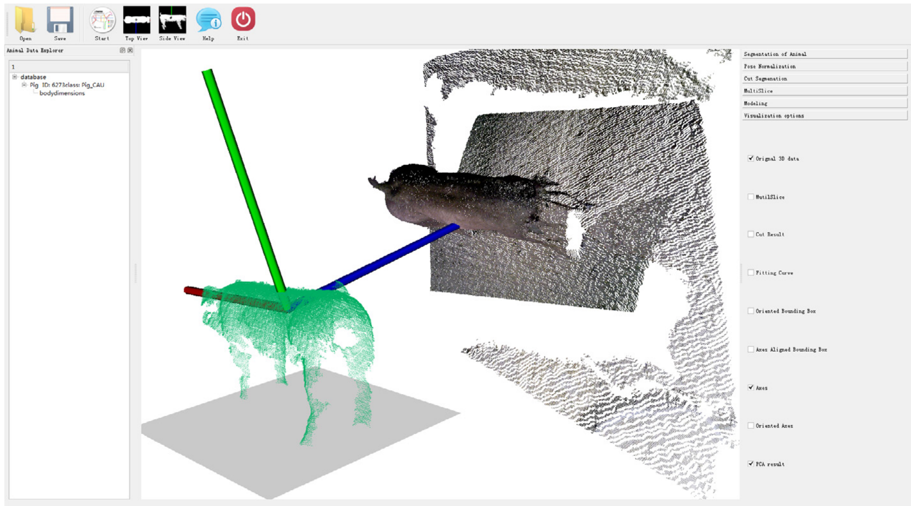


Fig. 7. Left: visualization of pose normalization result. Right: visualization of corresponding original input point clouds.

Note that above *x-y-z* related definition is with respect to canonical coordinate system. Based on these categories, each of them is corresponding to one measurement mode that added as a toolbar button to the LSSA_CAU user interface. So that users can switch among these categories before picking anatomical points for measurement, depending on the morphometric traits they need. Additionally, users are able to customize the traits name for each measurement. In this way, LSSA_CAU is able to be used for more livestock species and various morphometric traits.

2.3.3. Visualization and results management

To make LSSA_CAU user-friendly, we add 3D view, tree view for visualizing 3D point clouds and measurement results respectively. Specifically, PCLVisualizer class from PCL is employed to visualize 3D point clouds and process user mouse input event to acquire points needed for measurement. We integrate QTreeView with QStandardItemModel to visualize the measurement results by using model-view-controller (MVC) pattern. Xml data structure is used for management of livestock, traits name and its corresponding measurement. So that we can easily implement the functions of saving or opening the measurements file by using QDomDocument class from Qt.

2.4. Software validation

In order to test the software, point clouds of pigs were captured by using our prototype system for animal 3D reconstruction (Guo et al., 2014), and both these point clouds and synthetic data (pigs, cows, horse) were processed by using the LSSA_CAU. Additionally, each 3D reconstructed pig was manually measured for heart girth, height and body length and so on. To quantify the accuracy of the software measurement results on point clouds data capturing from our prototype system, the percent error $\mathbf{Pe}_i$ in one specific observation and in the average of all observations **Ave** were calculated. Moreover, the standard deviation **SD** of all observations was calculated to describe the difference between the traits from software and traits from manual measurement for each livestock were determined so as to validate the software.

$$\mathbf{Pe_i} = \frac{|x_i - \hat{x}_i|}{x_i} * 100\%,$$
$$\mathbf{Ave} = \frac{1}{N}\sum_{i=1}^{N}\mathbf{Pe_i}, \tag{2}$$
$$\mathbf{SD} = \sqrt{\frac{1}{N}\sum\nolimits_{i=1}^{N}(\mathbf{Pe_i} - \mathbf{Ave})^2}$$

where N is the total number of observations, x_i is the manual measurement for animal i, while $\hat{x}_i$ is corresponding measurement by the software.

3. Results and discussion

3.1. Components of the developed software

A screen shot of the software as a collage of some of its features is shown in Fig. 8. The software contains 38 events that include loading, rendering, segmenting, pose normalizing, measuring point clouds data, mouse, and keyboard activities coded in the form of subroutines to perform several actions. As shown in Fig. 8, the software is composed of main window, 3D visualization view, 1 toolbar with 14 tool buttons covering all measuring modes and all actions, 5 command buttons performing various actions, two floating panel displaying results and control parameters related with different operations respectively. The software also produces a xml format text file for the body measurements data and corresponding user defined data. Many actions are achieved by either clicking command buttons or selecting them through tool button or by shortcut keyboard combinations. Unit used in the software is same as loading 3D data. So are the output measurements.

3.2. Results on real world data (live pigs)

The first dataset we validate our software on is point clouds of live pigs. Specifically, ten Landrace pigs with long bodies, short hair ranging in age from 130 to 220 days were captured by using our prototype system for animal 3D reconstruction (Guo et al., 2014) at the ShangDong WeiHai swine-breeding center of DA BEI NONG GROUP. The heights of these animals were between 52 and 66 centimeters (cm), while their lengths varied from 80.5 to 104 centimeters (cm). Figs. 7, 5, 8 show results on each step of processing pipeline for one pig. Each subject of 10 live pigs was manually measured using the standard Lydtin stick in order to assess heights, widths and lengths while the circumference was evaluated through a tape meter. We performed the corresponding body measurements on point clouds data of these live pigs by using the software. Table 1 shows the comparisons between the mean value of live pigs body measurements measured manually and using our software. The segmentation results on these data are pretty good. While pose normalization results show that PCA based normalization method is heavily dependent on data. The data with non sym-

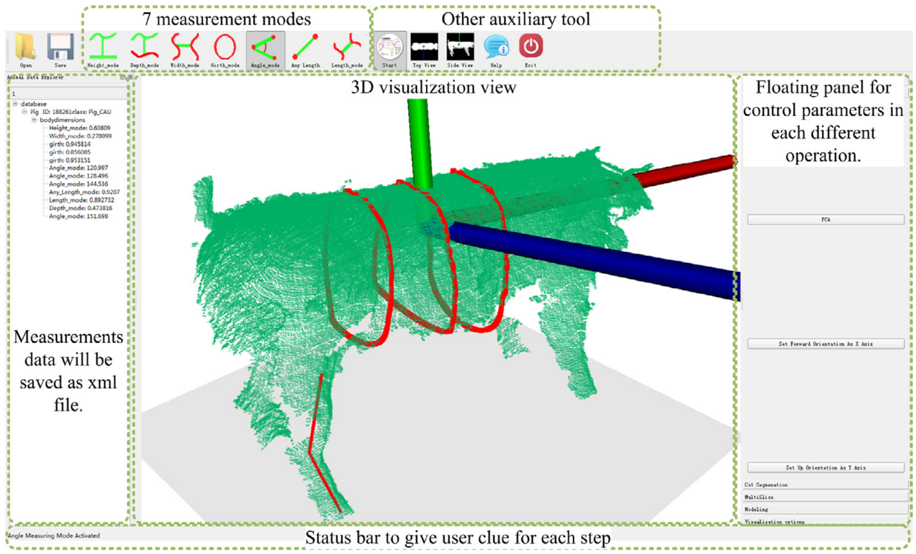


Fig. 8. Selected features of the developed livestock body measurement software.

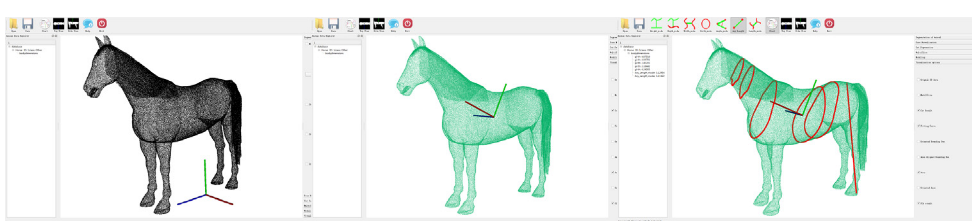
Table 1
Comparisons between the mean value of live pigs body measurements measured manually and using our software. **Average**: average percent errors for different traits on the 10 real world pigs. **SD**: standard deviation for corresponding percent errors.

Statistic (%)	Body length	Withers width	Withers height	Hip width	Hip height	Heart girth
Average	2.4	5.8	7.4	4.7	4.8	
SD	5.3	4.8	5.1	8.5	2.8	

metric missing parts or with pigs's head aside would produce bad pose normalization results, as shown in Fig. 10. Error percentage achieved demonstrated that our software can reach levels of measurement accuracy comparable to those obtained by traditional measuring instruments. It should be noted that more accuracy can be obtained by using more advanced 3D scanning system. However, heart girth cannot be measured correctly by software due to under-part missing issue that is caused by the limitations of our point clouds data acquisition method. In practical computer vision system, it is worth pointing out that the 3D/2D images of under-part of livestock are usually missed due to occlusion. So this problem can be solved by adjusting the curve fitting algorithm In the future.

3.3. Results on synthetic data (pigs, cows, horses)

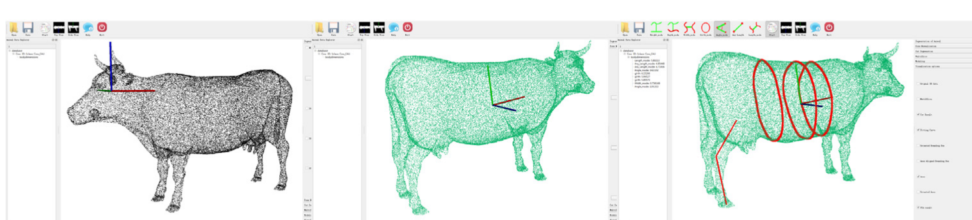
We performed experiments on the point clouds data of three livestock species from synthetic data, namely 2 pigs, 2 horses, 2



(a) Visualization of original horse data

(b) Visualization of pose normalization result on horse data

(c) Screen shot of body measurement result on horse data

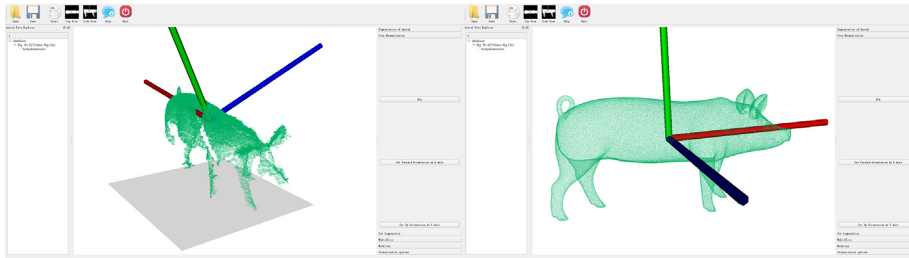


(a) Visualization of original cow data

(b) Visualization of pose normalization result on cow data

(c) Screen shot of body measurement result on cow data

Fig. 9. Visualization of entire pipeline on synthetic datasets. Note that there is no segmentation processing here.



(a) Pose normalization result on one pig data with holes due to occlusion

(b) Pose normalization result on synthetic pig data adhere to assumptions made in Section 2.1

Fig. 10. Non-symmetric data missing due to occlusion may lead to bad pose normalization results.

cows. Fig. 9 shows representative results for each species. It is worth pointing out that, comparing with current body measurement related reports (Viazzi et al., 2014; Tasdemir et al., 2011), most of traits can be measured easily with less user interaction in our software framework. For example, user can measure heart girth and body height with one clicked point only if the livestock is under canonical coordinate system. Besides, our software can handle more livestock species and various morphometric traits. However, the pose normalization results on horses data are not correct due to the fact that horse neck conformation is longer and horse head is upward.

In Fig. 10 comparative pose normalization results between real world pigs and synthetic pigs data, are illustrated. These normalization results show that the PCA based pose normalization method can produce accurate alignment results only if the pigs with her head straight forward. Additionally, data missing due to occlusion may lead to bad results. These assumptions would fail in most practical livestock farming scenarios. So the pose normalization method need to be adjusted in the future.

4. Future developments

The present public release of LSSA_CAU meets the major demands dictated by its development objectives. Short-term development goals include minor graphical improvements, automatically determining the positive direction of pose normalization results, addition of new measurement modes (geodesic distance, etc.), addition of new 3D file format, and addition of functions for measuring different livestock automatically. We also intend to improve our PCA based pose normalization method so as to solve the problem caused by data missing, strict assumption about livestock head pose. Depending on feedback from LSSA_CAU users we may consider also other development options. Another big issue of livestock body measurement based on point clouds is how to get the qualified point clouds of livestock automatically, will be next priority for researchers.

5. Conclusions

An interactive 3d point clouds analysis software for body measurement of livestock with similar forms of cows or pigs was successfully developed in C++ and tested. We have shown results on real world and synthetic datasets that demonstrate that our software is able to handle various livestock species by using a novel idea of integrating pose normalization and segmentation into the input data processing pipeline, our software can reach levels of measurement accuracy comparable to those obtained by traditional measuring instruments. However, in order to be more practical, PCA based pose normalization need to be improved so as to make the software more robust to livestock head pose and data missing issues.

Acknowledgments

The authors wish to thank everyone who participated in the software assessment, both taking 3d data and manually measuring traits. Thanks to ShangDong WeiHai swine-breeding center of DA BEI NONG GROUP they provide us materials for experiment. We also acknowledge the comments of the referees, which have significantly improved the text. This work was supported by National Natural Science Foundation of China [Grant No. 41601491]; National Key Technology R&D Program of China [Grant No. 2015BAH28F0103]; State Key Laboratory of Virtual Reality Technology and Systems, Beihang University [Grant No. BUAA-VR-16KF-16]; The Fundamental Research Funds for the Central Universities [Grant No. 2017QC061,2017QC057].

Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.compag.2017.04.014.

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