final report

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Prepared by: Dr Malcolm McPhee[1], Dr Alen Alempijevic[2]

NSW Department of Primary Industries Agriculture NSW[1], UTS Sydney[2]

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Value based trading system: image analysis of sheep and beef carcasses- proof of concept

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Abstract

This project has provided a 'proof of concept' for estimating lean meat yield (kg) and consequently retail beef yield in beef carcasses. The position of the RGBD cameras has been determined for the scanning of beef and sheep carcasses. Techniques presented in this report are also transferable to estimating lean meat yield and consequently retail yield in sheep carcasses. The curvature of the butt profile along with hot carcass weight produced a strong relationship between lean mean yield and the signature profile of the carcasses in 2 datasets; 2.97kg and 5.03kg root mean square error (RMSE) in estimating lean meat yield in cattle carcasses in slaughters conducted in Feb 2014 (n=32) and May 2014 (n=31), respectively. However, on this small dataset, muscle score and hot carcass weight (HCW) estimated lean meat yield marginally better than curvature and HCW. This result highlights the important role that muscle score plays in estimating phenotypic traits in beef cattle.

Executive summary

This research project conducted by Agriculture NSW in collaboration with the University of Technology, Sydney (UTS) has provided a ‘proof of concept’ for using 3D cameras to estimate lean meat yield in cattle. This project has built on earlier work by Agriculture NSW and UTS (B.BSC.0339) that provided a ‘proof of concept’ for estimating phenotypic traits in steers using 3D images.

In this study cattle were used because the estimation of lean meat yield and fat in Angus cattle was being undertaken within MLA project B.SBP.00111. However, equipment developed by UTS, to stream line the process of data collection has been demonstrated on a sheep carcass.

In this report, we present regression results for Feb 2014 and May 2014 carcasses on steers and heifers. Throughout the analysis bias has been minimised by stratifying the training and testing sets through random sampling to help ensure that each class is properly represented in both training and testing sets. To validate our approach 50 x 10-fold Gaussian Regressions were performed using a combination of muscle score, live weight (kg), hot carcass weight (HCW) (kg), and primal weight (kg) (i.e., blade, brisket etc.) to estimate lean meat yield (kg).

Conclusions

- The position of the RGBD cameras to develop 3D images on carcasses has been determined.
- Specialized equipment that can be used on either beef or sheep carcasses has been developed to automatically scan a carcass and provide consistent quality data.
- Estimating muscle score by using 3D cameras is important in the prediction of phenotypic traits.

This study found that a method to estimate lean meat yield (kg) and consequently retail beef yield using data gathered from a hand held RGBD camera and software is capable of producing a full 3D model of a carcass. A data driven supervised learning approach employing state of the art classification and regression techniques was used for this purpose. The results indicate that there was a 2.97kg and 5.03kg root mean square error in estimating lean meat yield in Feb 2014 (n=32) and May 2014 (n=31), respectively. However, on this small dataset muscle score and HCW estimated lean meat yield marginally better than curvature and HCW.

Recommendations

Future work should focus on the following key areas of research.

1. Analysis based on gender and different breeds;
2. Evaluation of equipment developed by UTS to produce a more complete and accurate 3D model to estimate lean meat yield (kg) for sheep and beef carcasses; and
3. Investigation of combining curvature with volume and colour.

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1. Background

Estimating lean meat yield for both the sheep and beef industries has the potential to increase profitability for the red meat industry. A ‘proof of concept’ of using off the shelf 3D cameras to estimate phenotypic prediction traits in beef cattle has proved to be feasible. Therefore, a study investigating the ‘proof of concept’ of estimating lean meat yield for carcasses was conducted. Beef carcasses rather than sheep carcasses were used for the evaluation because a study on beef carcasses was already underway. The methodologies developed would be transferrable between beef and sheep.

2. Project objectives

1. Determine the position of the RGBD cameras to obtain optimal 3D images of carcasses (beef and sheep).

2. Develop a relationship between the 3D images from the RGBD cameras and the measured total fat and lean from the CT scanner to predict retail beef yield.

3. Evaluate the potential of the imaging data to predict retail beef and lean meat yield in sheep.

3. Methodology

Data, using RGBD camera technology and data acquisition software systems, was collected from John Dee abattoir, Warwick, Queensland on 19 steers, and 13 heifers (Feb 2014) and 19 steers, and 12 heifers (May 2014). Phenotypic data collected prior to slaughter included: weight (kg), scanned P8 fat (mm), rib fat (mm), eye muscle area (cm^2), intramuscular fat (%), hip height (mm) and estimates of muscle score by trained assessors.

After slaughter carcasses moved along the chain and ended up in the chillers where RGBD imaging of the left carcass was undertaken. The left carcass did not have any fat trimmed from the carcass and only hygiene fat trim was removed where necessary. The left carcass, on the following morning, were deboned and cut into specific primals as per a pervious CRC marbling experiment. Primals were then transferred back to the University of New England Meat Science lab and then CT scanned so that both fat and lean meat yield could be estimated. Statistics of Live Weight, Muscle Score and Lean Weight for Feb 2014 and May 2014 carcasses are presented in Figures 1, 2 and 3 respectively.

Capturing data

A RGBD Primesense (Model: 1.09) handheld device was used to capture data. This camera has a minimal range of 20cm and therefore provided images of carcasses within the constraints of the abattoir processing system (ie: proximity of walls/other carcasses in the chillers). Obtaining the inner and outer surface of the carcass involves obtaining data from a number of camera positions.

To generate a complete 3D model of the left side of the carcass individual RGBD images were fused together using a technique that exploits both RGB and 3D data in an optimization framework. Achieving the fusion for one side of the carcass required having to expose each area of the carcass to the camera with a small overlap, thus, scans were performed in a zig-zag fashion from top to bottom (a similar pattern to spray painting a rigid body). In order to make this process computationally tractable, as the optimization needs to be undertaken in real-time, the spatial resolution of the 3D data was set to a hard limit of 5mm. For each voxel (5mm*5mm*5mm point) the 3D data was married with a RGB colour resulting in surfaces such as those in Figure 4 (left: external with colour, centre: external with only 3D data, right: internal with colour).

Therefore, the following steps were taken to collect the data:
(1) Outside of the carcass was scanned (top to bottom).
(2) Carcass was rotated and held still.
(3) Inside of the carcass was scanned (top to bottom).

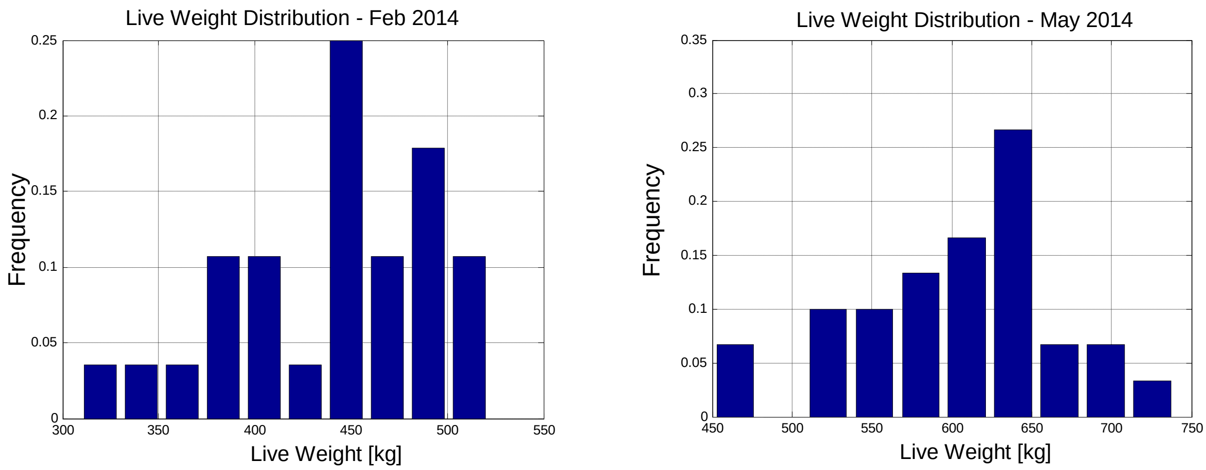

Figure 1- Live Weight Distribution

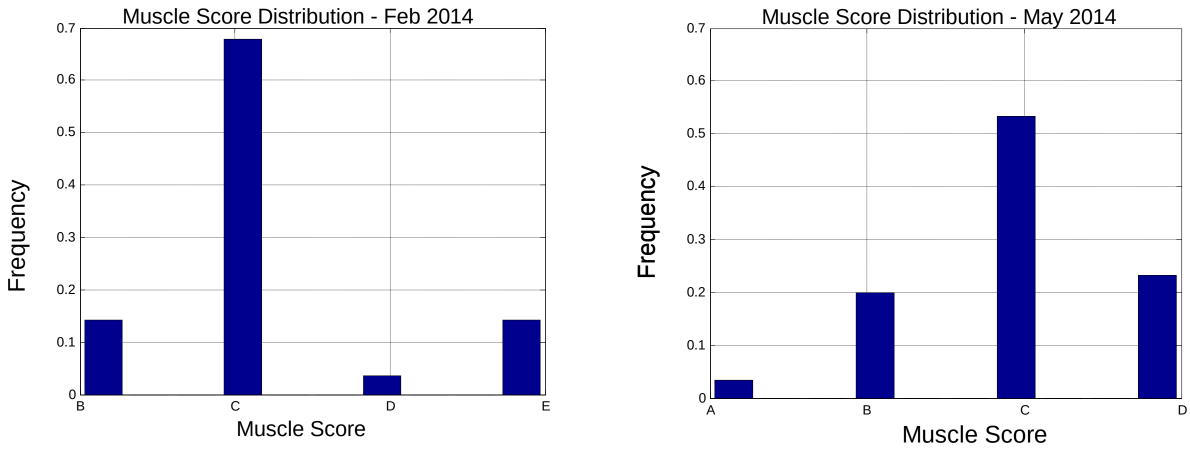

Figure 2 - Muscle Score Distribution

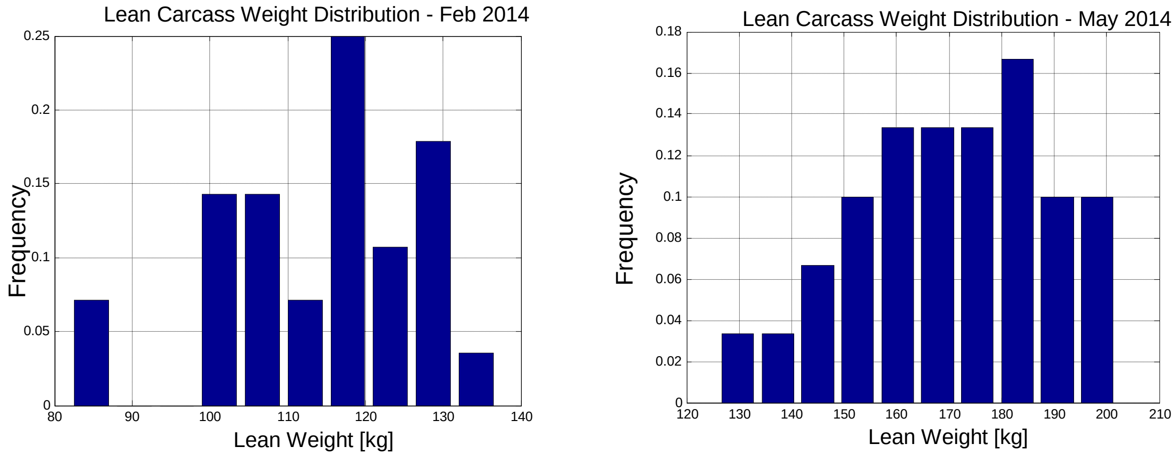

Figure 3 - Lean Carcass Weight Distribution

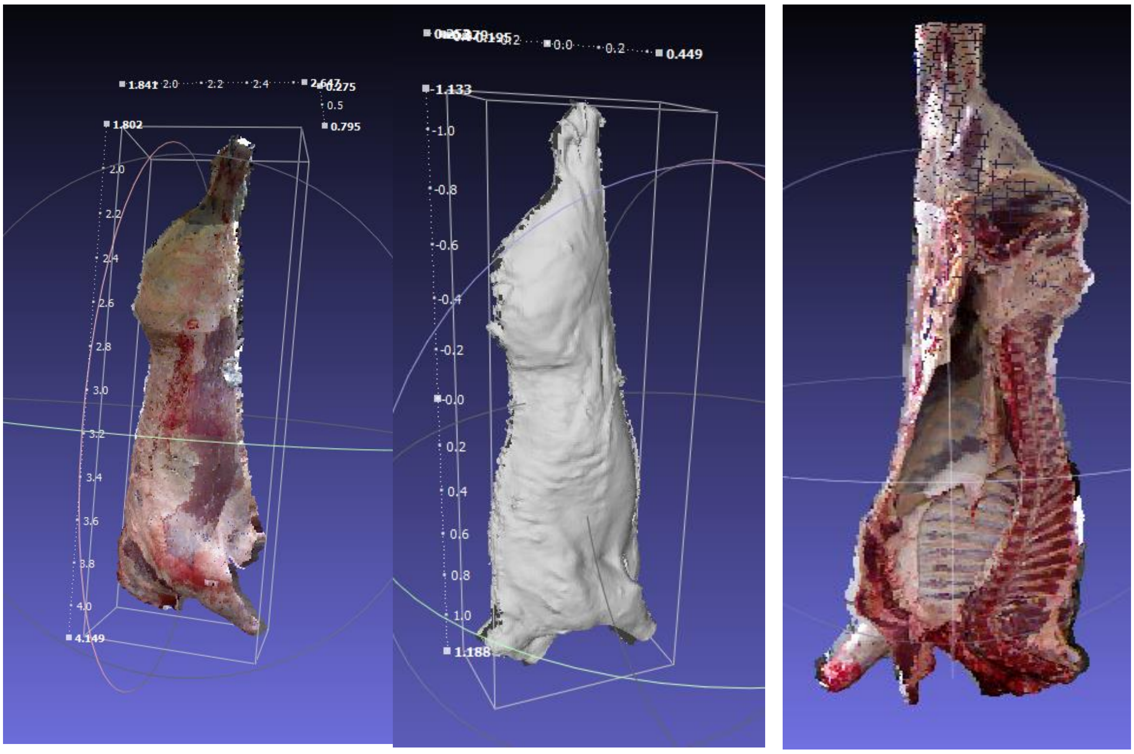

Figure 4 - sample 3D model of carcass: (left) exterior with RGB colour, (middle) exterior with 3D data, (right) interior with RGB colour

Processing Pipeline

In order to determine representative 3D information of cattle with respect to the estimation of lean meat this project has investigated the possibilities of extracting descriptive information of the entire carcass (internal and external) via volume / area / shape - curvature / shape – 2D profile and colour or combination thereof. Similar to our approach in MLA project B.SBP.0085, subsets of the entire volume of 3D shape, were evaluated in relationship to lean meat. The body of work undertaken prior to this study (MLA project B.SBP.0085) indicated the focus should be on the forequarter and hindquarter areas with special reference to the shape of the butt. The processing pipeline is depicted in Figure 5.

The processing pipeline (Figure 5) from RGBD data acquisition through to the estimation of lean meat starts with acquisition of RGBD data from the hand held RGBD sensor and assembling a 3D model with colour already described in the capturing data section. It is essential that sufficient coverage of the entire carcass is completed as consistency is essential for any successive processing step. The second step of this processing pipeline is transforming the information from all carcasses into a common coordinate frame tied to the position of the hook suspending the body on the processing chain. This step allows consistency in analysis over future parts of the processing pipeline.

A manual step of extracting smaller volumes of interest across all carcasses was then conducted, to effectively separate regions containing several muscle groups. Developing an automated tool to assist in collecting quality data was outside the scope of 'the proof of concept' and is commented on later in the report. Note: the approach taken to analysis also restricted any subsequent processing to the hindquarter area as consistency in extracting similar regions across carcasses ensures correct subsequent interpretation. As already reported in Milestone 1 of this project the thresholds in separating these volumes were empirically assessed, identifying the 12th rib on the 3D models and using the distance from hook to the 12rib and overall animal height ensured some consistency within each month (Feb and May).

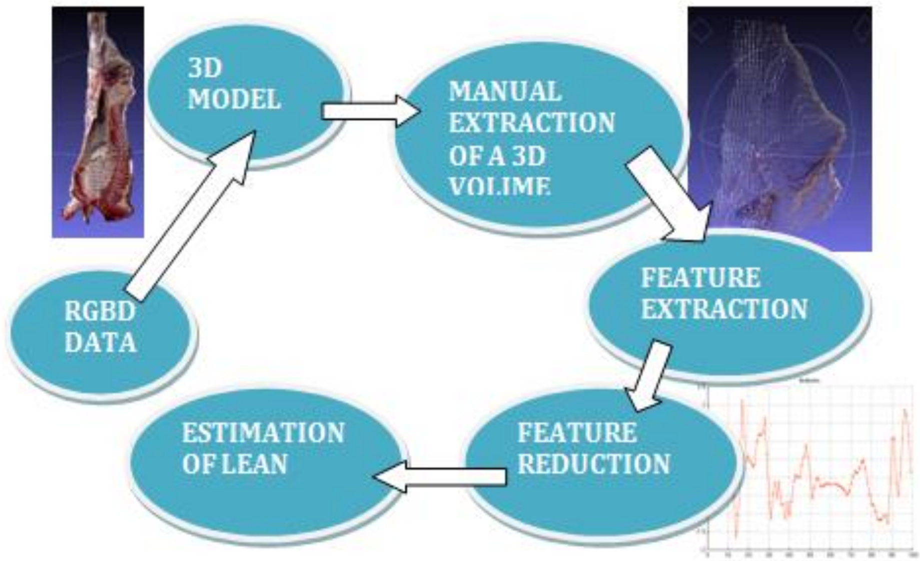

Figure 5 - Simplified Processing Pipeline

The manually extracted 3D volume is then transformed into a compact signature (feature extraction). This project has evaluated a number of approaches that examined colour (normalised RGB and HSV colour space), surface length / volumetric information, surface curvatures and combination thereof. The feature extraction and reduction steps produce a compact and information-rich representation of the raw point cloud data collected for each carcass (Figure 5).

From the number of features examined the best performance in terms of root mean square error (RMSE) of the final estimated and measured Lean were obtained using the surface curvatures extracted from a subset of the 3D volume identified as the area describing the "butt shape". However, surface curvatures alone are not able to estimate lean and a twofold step was employed to devise this relationship. The curvatures devised under MLA project B.SBP.0085 are suitable to encompass a trait (such as muscling) and are scale and rotationally invariant, to be able to deal with animals moving through a race. Translation from muscling score to lean value (kg) requires prior knowledge of the animal weight (either Live Weight or Hot Carcass Weight). For instance Table 1 contains data from May 2014 of two animals with a disparate Muscle Score (and Muscle %) of B- and D-. However, the Lean of the Left Side of carcass is 82.25kg and 104.29kg, live weight 544kg and 740kg respectively. Therefore a method to add the live weight into the feature vector in addition to surface curvatures was devised in the feature reduction step.

Table 1 - May 2014 Data (Sample of two animals)

ID	Live Weight (kg)	Fat (kg)	Lean (kg)	Hot carcass Weight (kg)	Primal Weight (kg)	Muscle %	Muscle Score
86	544	34.27	82.25	153	149.91	54.87	B-
88	740	46.57	104.29	202	198.12	52.64	D-

To allow addition of weight and overcome the large dimensionality space of the feature vector (n=308) with respect to the small dataset (m=32) an optimization step via Genetic Algorithm as reported in B.BSC.0339 was employed to reduce the feature vector size (number of dimensions n) with respect to the discriminative power to estimate Muscle Score. This allowed adding weight (either Live Weight or Hot carcass Weight) as another element of the feature vector to allow estimation of lean. The Genetic Algorithm indeed did confirm that weight was essential in the feature vector composition.

At this stage of the processing pipeline there exists a single signature for each carcass in the data set. All the signatures are then assembled into a feature vector (surface curvature + weight) as separate instances for each carcass. The production of a feature vector is the final stage of taking the transformed point cloud data and arranging it into a form that is amenable to the machine learning environment, as illustrated in Witten, Frank, Hall (2011).

Table 2 - Feature vectors containing a single signature and associated class label for each carcass in the dataset

Surface Curvature 1	Weight 1	Lean 1
Surface Curvature 2	Weight 2	Lean 2
...	...	...
Surface Curvature n-1	Weight n-1	Lean n-1
Surface Curvature n	Weight n	Lean n

The feature vector is then used as input for training a machine learning algorithm known as Gaussian Process Regression which is a state of the art supervised learning method. The training/testing approach proposed involves supervised learning, which infers a function from the "labelled" instances (i.e., observed values) of Lean in the feature vector, refer Table 2. In summary, the input to the machine learning scheme is expressed as a table of independent instances of the point cloud representation of each animal (the concept) to be learned. Once the machine leaning (ML) algorithms have been trained on a subset of the feature vectors, a non-linear mapping between the statistical-based surface curvature signature/weight and the provided class label Lean is learnt. Using a smaller test subset of unseen instances, predictions can then be made on the Lean (kg) of those animals present in the test set.

The accumulation of inputs: 3D point cloud data and weight (i.e., feature vector) and the observed values Lean(kg) are used to construct a sensor model. Once built, the sensor model can be used to produce the appropriate classification or regression on the presentation of an instance vector gathered from a new animal.

The approach consists of getting a sensor model to learn to characterise the feature vector as inputs. We make use of the observed subjective muscle score data to build these models in a supervised learning manner as follows:

Step 1: Acquire 3D point cloud data in the abattoir, weight (live or hot carcass weight) and Muscle Score;

Step 2: Extract a representative volume from the hindquarter area of the carcass;

Step 3: Reduce the high dimensionality of the point cloud data by extracting features from the input signals to produce a compact and representative feature vector;

Step 3: Perform global optimisation of the feature-vector signatures using the parallel genetic algorithm with respect to Muscle Score to reduce the feature vector;

Step 4: Train a sensor model based ‘exclusively’ on the feature vector and weight (Live Weight or Hot Carcass Weight) with respect to Lean [kg] for each animal in the data set;

Step 5: The learned models can then be used to infer measured Lean [kg] from new point cloud data and weight (Live Weight or Hot Carcass Weight) ***without the need for any input from trained assessors***;

Regression experiments were performed using 50x10 Fold Cross Validation randomised Gaussian Process learning scheme. That is 90% of the data was provided to train the model and 10% was used as a challenge (test). This was performed 50 times using a completely random selection of training / challenge scheme, thus, providing an unbiased training and testing arrangement of the independent data sets.

4. Results

With any data driven machine learning technique it is desirable to have a large sample size distributed equally over the estimated values for Muscle Scores and Lean. It is important to realise, that the confidence of regression experimental results decrease with smaller sample sizes and unequal class or measurement distributions (Witten, Frank, Hall 2011), both of which are characteristics of the carcass data sets. There exist significantly overrepresented classes and measurement bands. We have attempted to minimise the bias caused by the instance distribution by stratifying the training and testing sets through random sampling to help ensure that each class is properly represented in both training and testing sets. In this report, we present regression results for Feb 2014 and May 2014 data.

To validate our approach 50 x 10-fold Gaussian Regression were performed using a combination of Muscle Score , Live Weight, Hot Carcass Weight, Primal Weight and Estimating Lean and are reported in Table 3.

The RMSE reported with the application of surface curvatures could be attributed to a number of reasons on the current data acquisition, volume extraction analysis. These results should be considered together with Figures 6 and 7 that reveal where the largest errors exist. It is evident that incorporating information from Steers and Heifers which also have large variations in Live Weight causes the Gaussian Process model to attempt to overgeneralise for the entire population. However, reducing the number of samples from 32 to 19 is also prohibitive; the sample size is also very small. The results of Table 3 also show that estimating Lean with Muscle Score and Hot carcass Weight of animals can also be used to produce an estimate of Lean (RMSE 2.82kg and 4.98kg for Feb 2014 and May 2014 respectively) using a Gaussian Process approach.

Table 3- Root mean square error (RMSE) for estimation of Lean (kg) using Gaussian Processes; independent observations for carcass data in Feb and May 2014 are reported

Date	RMSE [kg]	Inference	Observations
Feb 2014	2.81	Lean	Muscle Score / Primal Weight
Feb 2014	2.82	Lean	Muscle Score / Hot Carcass Weight
Feb 2014	2.97	Lean	Curvature / Hot Carcass Weight
Feb 2014	3.40	Lean	Curvature / Live Weight
Feb 2014	3.70	Lean	Primal Weight
Feb 2014	4.14	Lean	Muscle Score / Live Weight
Feb 2014	4.54	Lean	Live Weight
Date	RMSE [kg]	Inference	Observations
May 2014	4.97	Lean	Muscle Score / Primal Weight
May 2014	4.98	Lean	Muscle Score / Hot Carcass Weight
May 2014	5.03	Lean	Curvature / Hot Carcass Weight
May 2014	5.52	Lean	Muscle Score / Live Weight
May 2014	5.65	Lean	Curvature / Live Weight
May 2014	6.02	Lean	Primal Weight
May 2014	6.46	Lean	Live Weight

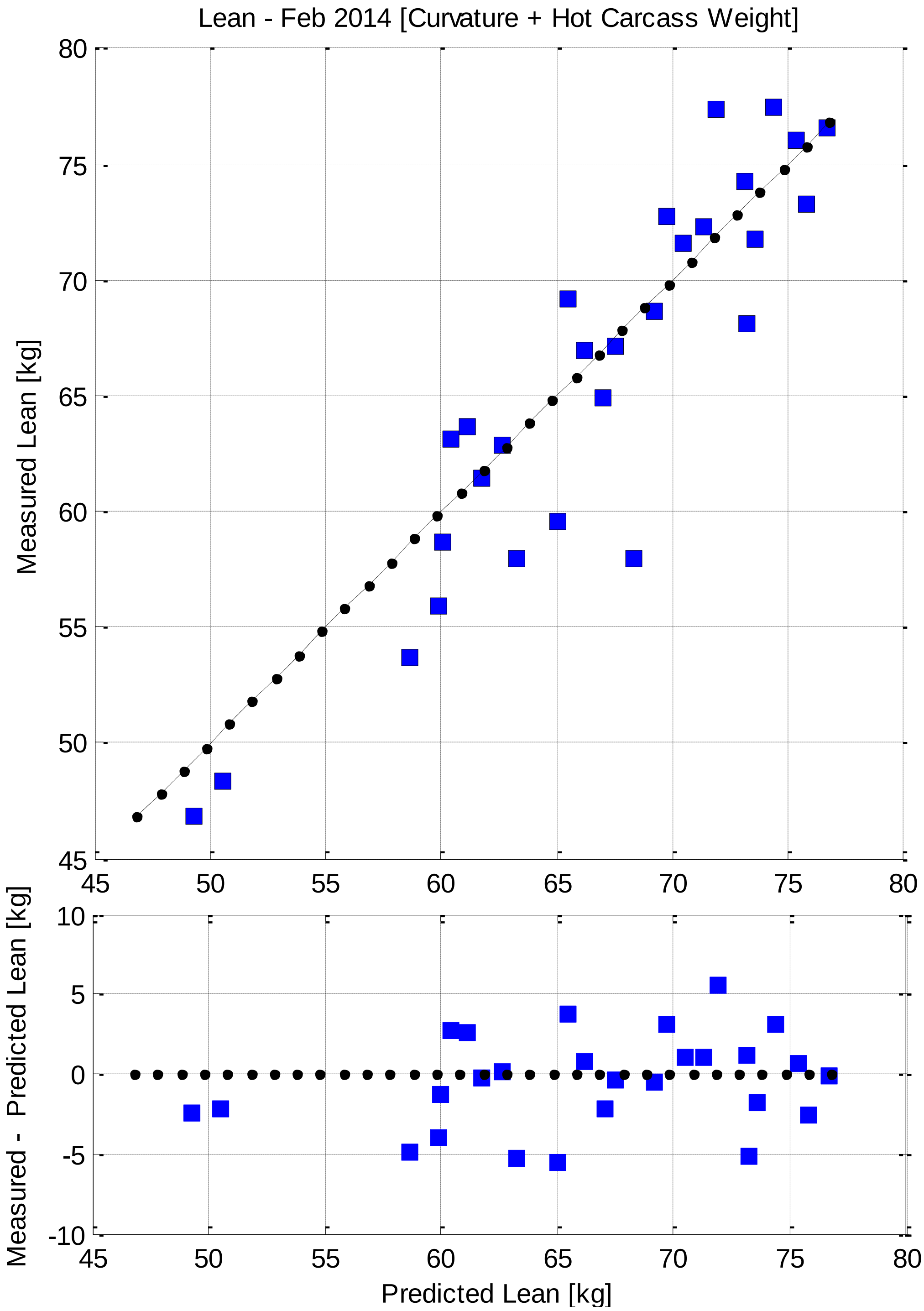

Figure 6 - Lean Estimation for Feb 2014 carcasses

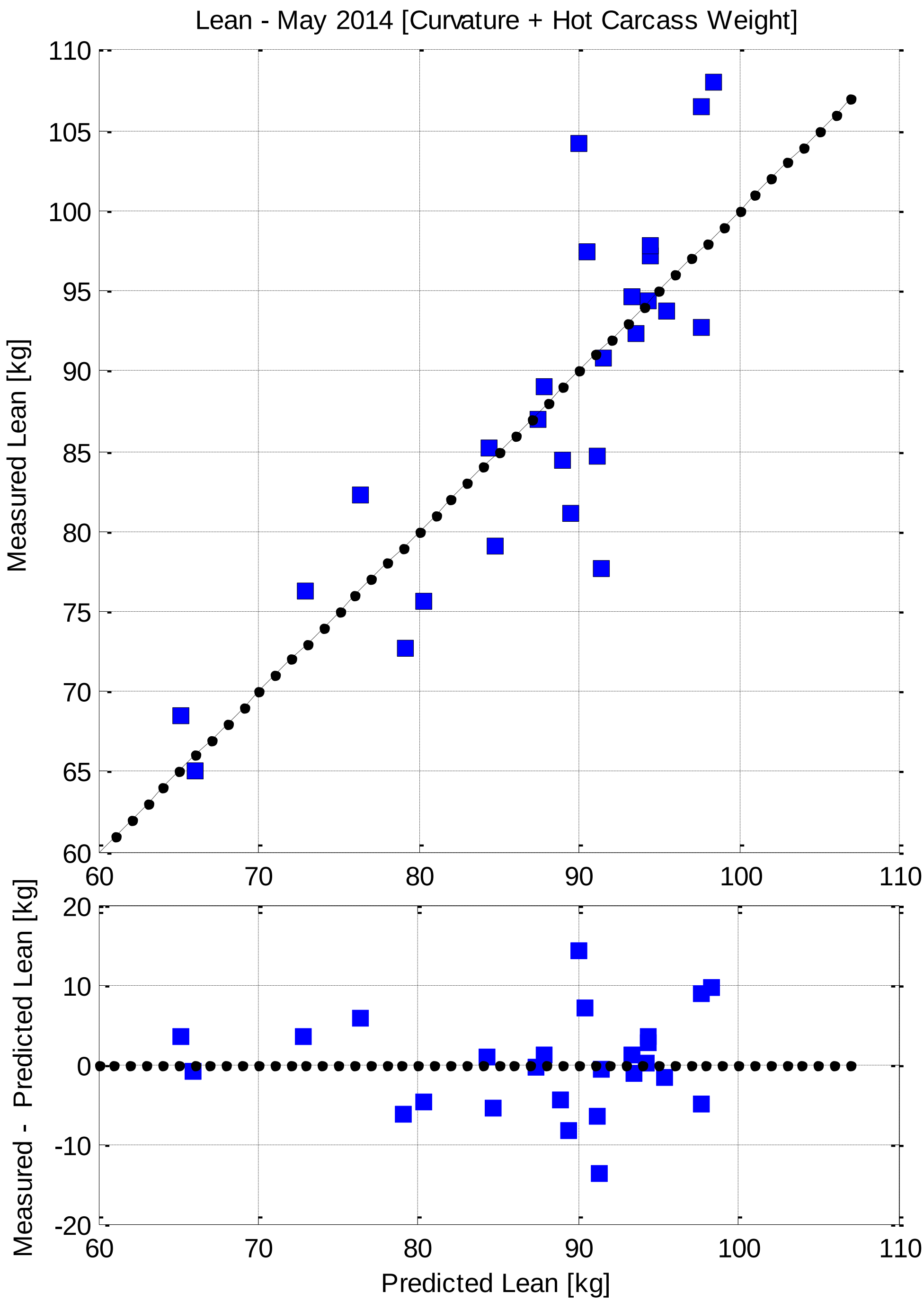

Figure 7 - Lean Estimation for May 2014 carcasses

Inconsistency in the volume extracted were noticed in the RMSE using the ID's of the animals (Figure 8) and the 3D model. We observe that animal 13 (animal 93 in kill) as being identified as having a predicted Lean value lower than measured. The volume used for surface curvature based on height from hook (red on Figure 9) was not consistent as encompassing the same volumetric area across all animals (refer Figure 9). The red line is the hardcoded extent (height considered for estimation) while the yellow line denotes the height required to allow consistency across all other animals. The overall height of the carcass did not show any significant difference, however the length of this area differed substantially. A linear equation between height of carcass and the extent of the volume from the hook does not capture this phenomena and extraction of the volume specific from each animals based on 3D data alone is warranted.

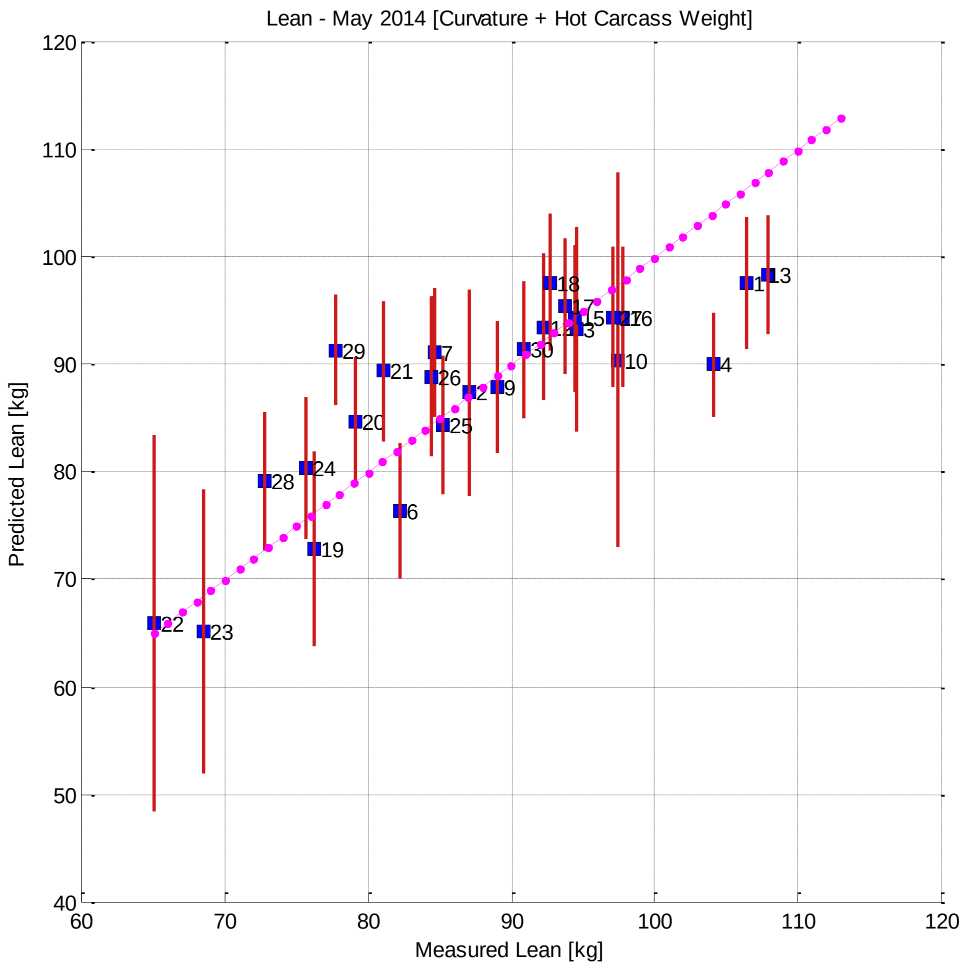

Figure 8 - May 2014 Estimation of Lean, IDs of animals noted with 2 sigma bounds from GP

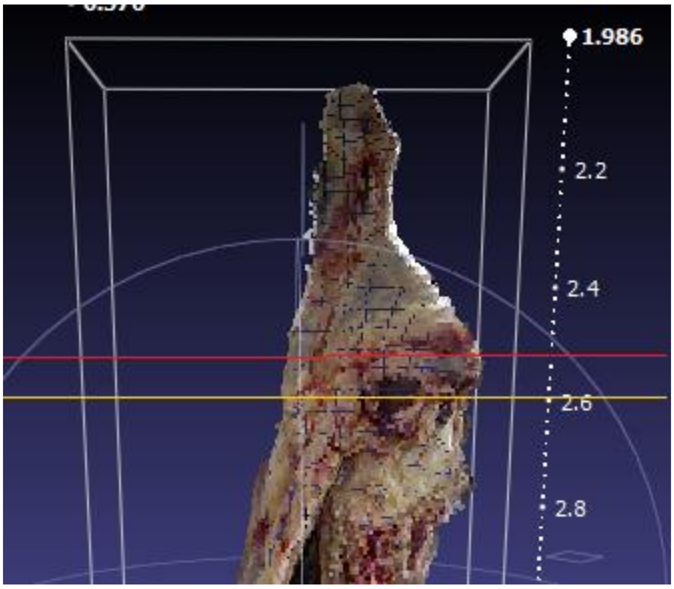

Figure 9 - Inconsistent height to cut butt profile (May14, Animal 93)

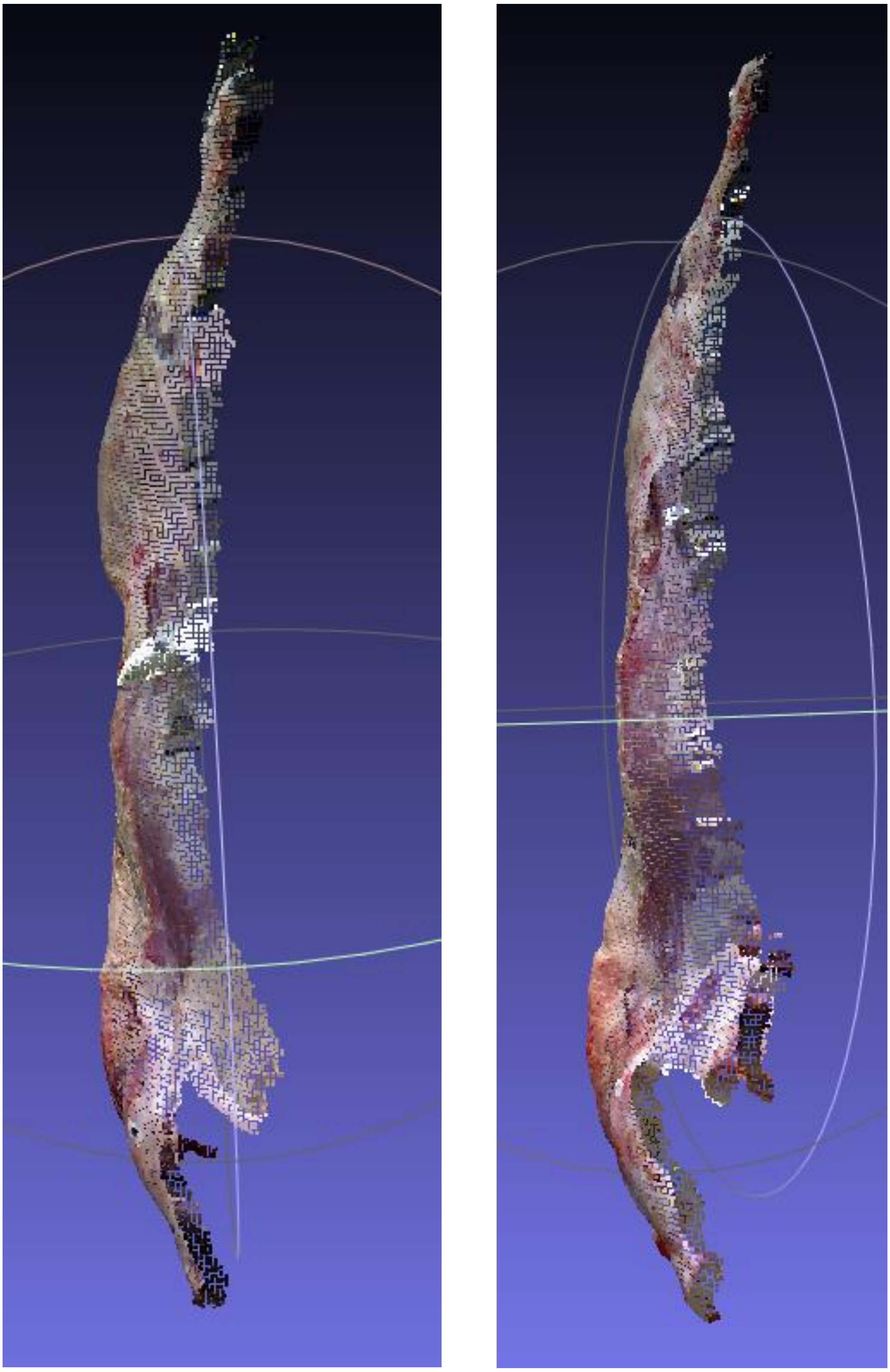

Figure 10 - Views of outer side of carcass; carcass 86 (left) and 88 (right)

Finally, we also comment on using surface curvature from the outside scanned area of the carcass and the possibility of computing volume for use in estimation of Lean using forequarter. The efforts to obtain the 3D model by moving the scanner and holding the animal had made the task of computing volumes over the hindquarter extremely challenging and prone to error. Fig 10 demonstrates that data was not obtained on the very edges of the carcasses, thus not allowing for the two sides (inside/outside) to be fused into a single representation allowing computation of volumes. The figure is also indicative of the difference in the hindquarter volume (thickness) between these animals with vastly different muscle scores.

Carcass Scanner

An automated scanner was devised (Fig 11) to be able to circumvent identified these challenges in obtaining a full scan of the carcass by simultaneously scanning the inside and outside of the carcass from three poses and moving the cameras in a circular fashion to allow the carcass to enter the scanner along the processing chain.

Figure 11 - Prototype development of automated scanner

A demonstration of the equipment on scanning a sheep carcass was conducted at Meat Sciences Lab in Armidale (UNE) on 5th December 2014. The scanner performed an automated scanning process, the system of 3 cameras scanned the carcass from top to bottom in 80 seconds while data was continuously streaming from the RGBD cameras Figure 12 and simultaneously the 3D model was captured in real-time as per Figure 13. Following, the scanning, the system rotated 60 degrees to allow the carcass to exit along the chain and then reverted to the original configuration (taking 18 seconds). The total time to scan the carcass was 98 seconds; the time limitation is imposed by current servo configuration. With a redesign the total time could be reduced to 10 seconds.

The system was demonstrated on a carcass that was stationary during the scanning process. It is foreseeable that the system can perform a scan of a moving carcass (swaying on the chain) with the inclusion of a Simultaneous Localization and Mapping (SLAM) process as per our previous work published in Ellekilde et.al

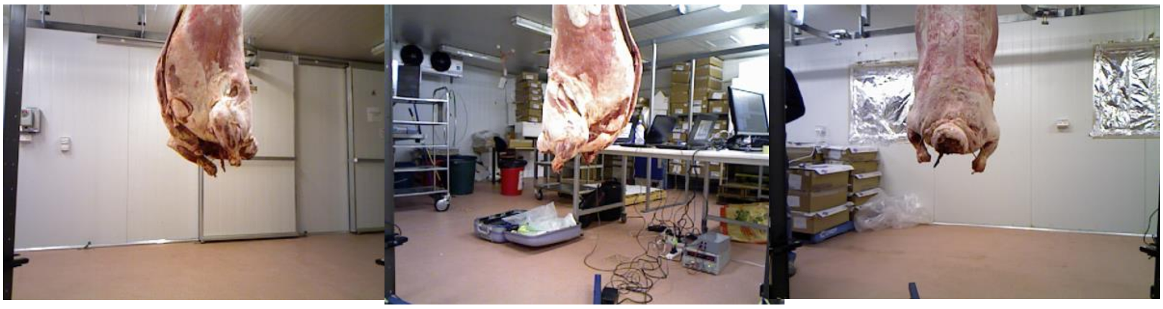

Figure 12 - Sample of the stream from 3 RGBD cameras

Figure 13 - Samples of scanned lamb carcass, two views from 3D model with colour

The current scanner is still in proto-type stage and on review of all the requirements on speed of scanning and rigidity of construction our recommendation would be to remove the need for caster wheels with a better designed base (box truss to reduce weight) as per Figure 14.

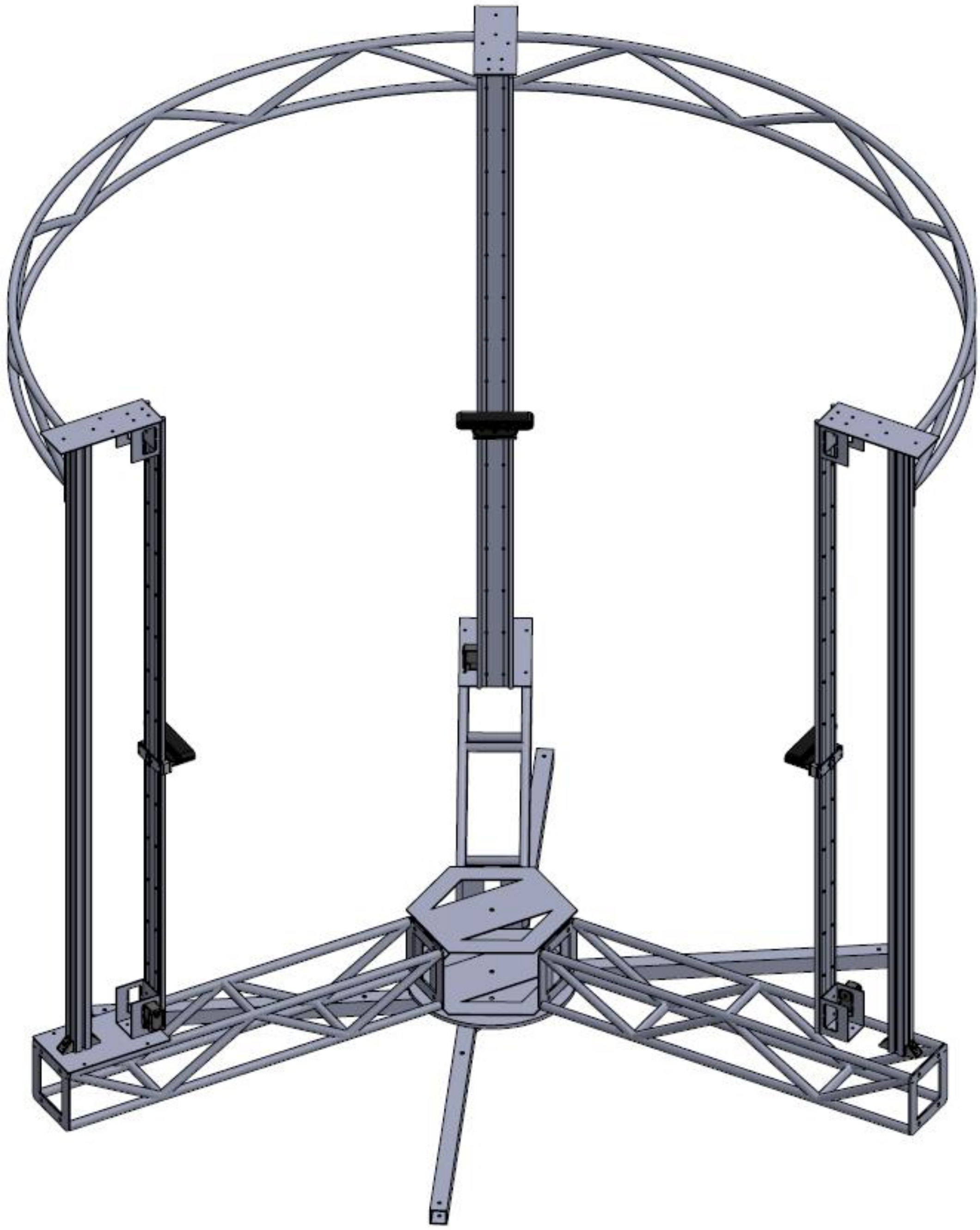

Figure 14 - Revised design for scanner

5. Conclusion

In this study, we have developed a method to estimate Lean (kg) using data gathered from a hand held RGBD camera and software capable of producing a full 3D model of a carcass. A data driven supervised learning approach employing state of the art classification and regression techniques was used for this purpose. Data obtained shows 2.97kg and 5.03kg root mean square error in estimating Lean Muscle in Feb 2014 and May 2014, respectively. However, on this small dataset muscle score and hot carcass weight (HCW) estimated lean meat yield marginally better than curvature and HCW. This result highlights the importance of providing the industry with an automated way of estimating muscle score as demonstrated in MLA project B.BSC.0339.

Further work needs to be undertaken confirming that the results presented here will generalise on a broader population of steers. In this study the February 2014 data for cows and May 2014 data for steers and heifers have been used. Further studies using the estimation of Muscle Score on Live animals in the field (completed for May 2014) could look at the impact of the estimated Muscle Score based on gender to validate impact on generalisation.

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