
# FEATURE EXTRACTION FROM RADIAL DESCRIPTOR LINES FOR BODY CONDITION SCORING OF COWS

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***Abstract.***

*Body condition score (BCS) is considered as one of the most important indices for managing dairy cows, which is used to evaluate fat cover and changes in body condition. Dairy farmers should be aware of their cows BCS to be able to identify the patient cows on time and manage diets when needed. In this study, we have introduced a new index which uses Radial Descriptor Lines (RDL) for BC scoring. Based on the fact that the fatter the cow the smoother the back surface, we hypothesised that the changes on the cow's back at different BCSs could be tracked through the changes on the radial lines centred on the hook bone emitting outward on the surface of the cow's back.*

*Images were captured using a Kinect sensor installed in the milking parlour of a dairy farm. To provide the required data for model development and assessment, 165 images were captured from 55 cows with different BCSs. Algorithms were developed in MATLAB environment. The consecutive steps designed in the algorithm were firstly distinguishing the hook bone based on the local maxima on the depth data taken from the Kinect sensor from the cow's back. Secondly, radial descriptor lines were taken out of the back surface with interval angles of 1 degree outward the hook bone toward the edges of the cow's back. Overall variations of the descriptor lines respect to a polynomial modelled datum line were measured and used as the extracted features. To include the most related and exclude non-related variations from the BCS estimation model, four orders (from 2 to 5) of polynomial datum curves were tested.*

*Effective features were selected using correlation-based feature selection (CFS) and fed to artificial neural networks to provide the corresponding BCSs. Results showed a correlation between the estimated BCSs from the model and the scores determined by the experts with a coefficient of determination ($R^2$) of 0.87 and a root mean square error (MSE) of 0.036.*

***Keywords.*** *Kinect, 3D imaging, machine vision, dairy, livestock management, artificial neural network*

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## Introduction

Body condition score (BCS) is one of the most important indices in the management of dairy cows. It is used for managing the calving, feeding, lactating and health monitoring of cows (Stockdale, 2008). Since BCS is manually determined by experts it is subjected to the person scoring, expertise, and consistency between scoring periods. Therefore, introducing an automatic BC scoring will not only cover the mentioned problems but also provide a fast and economical method of scoring which can be accomplished simultaneously with other activities in the parlour. Automatic body condition scoring has been attempted in several research studies.(Azzaro et al., 2011; Bercovich et al., 2013; Halachmi, Polak, Roberts, & Klopcic, 2008; Hansen, Smith, Smith, Jabbar, & Forbes, 2018; Spoliansky, Edan, Parmet, & Halachmi, 2016)

While different parts of cow's body might be considered for BCS, cow's back is the most common area which distinctly reflects the condition changes and has been used in several research studies (Bewley et al., 2008; Coffey, Simm, Oldham, Hill, & Brotherstone, 2004; Fischer, Luginbühl, Delattre, Delouard, & Faverdin, 2015; Weber et al., 2014) Taking two dimensional (2D) images from cows with normal RGB cameras are useful specifically when changes in the shape boundaries are targeted (Azzaro et al., 2011; Bewley et al., 2008). Estimation of the live weight or BCS based on 2D images needs also to address the perspective problems; for example by using a supplementary device such as a telemeter to measure the distance of the cow to the camera (Negretti, Bianconi, Bartocci, Terramoccia, & Verna, 2008).

To enhance the segmentation of cows body from the background, thermal imaging may also be used (Halachmi, Klopčič, Polak, Roberts, & Bewley, 2013)

Three dimensional (3D) images have the benefit of adding the depth information to the images. Among several ways of taking 3D images, Kinect sensor (Hansen et al., 2018; Nir, Parmet, Werner, Adin, & Halachmi, 2017; Salau, Haas, Junge, & Thaller, 2017; Van Hertem et al., 2017) stereo vision (Azouz, Esmonde, Corcoran, & O'Callaghan, 2015) and time of flight camera (Nir et al., 2017; Weber et al., 2014) have been used for body condition scoring of cows.

The change in the cow's body contour in a binary image, is a source of information for extracting the features correlated to BCS. Fourier descriptors of cow signature are also a set of features used for enhancement of scoring algorithm. They are effective tools for describing the variances of centroid- boundary distances. (Bercovich et al., 2013) used the absolute values of the first 10 Fourier descriptors of the cow's signature in a linear regression model to predict the BCS which raised the performance up to R2=0.77. Since BCS is a measure for changes of the body mass every correlated change might be considered as a feature reflecting the BCS changes. These features can be derived from deviations of the boundary respect to baselines (Weber et al., 2014) or resembled shapes such as parabola (Halachmi et al., 2013) or ellipse (Nir et al., 2017).

By a hypothesis that a fatter cow has a more rounded body than a thin cow, (Halachmi et al., 2013) designed an algorithm to use the deviation from a parabola as a measure for BCS estimation. The total mass of a heifer could also be estimated by fitting an ellipse to the contour of cow's body in 2D binary images (Nir et al., 2017).

## Material and methods

In this study, to design an algorithm for the automatic determination of body scores, from cows, the Holstein breed was photographed at Pegah Dairy Farm in Fars province, Iran. Images were captured from the top view of the cows' waist using a three-dimensional Kinect sensor installed at a height of 2.5 m in the milking parlour of a dairy farm. At the same time of imaging, two experts were recording the scores of the cows. Each cow was photographed 7 times. Three images were selected as replications from each cow. To provide the required data for model development and assessment, 165 images were captured from 55 cows with different BCSs.

Algorithms were developed in MATLAB environment and the results were analysed with SPSS software ver.21 Weka ver. 3.8.2.

The area between the bones of the hook and the bones of the pin is the main important area of the cow's body which has the most information on obesity and animal fat. As a preprocessing step, redundant objects in the image such as background and parlour bars were removed from the image. To do this, at first, using depth information, points with a distance of more than 130 centimetres to the camera were removed from the image. Severe dilation and erosion operations were done to remove the remaining objects from the image.

During data capturing some points with missing depth values may appear in the point clouds which show NaN values in the resulted image matrix. These points were first identified and then their values were corrected using nonlinear interpolation.

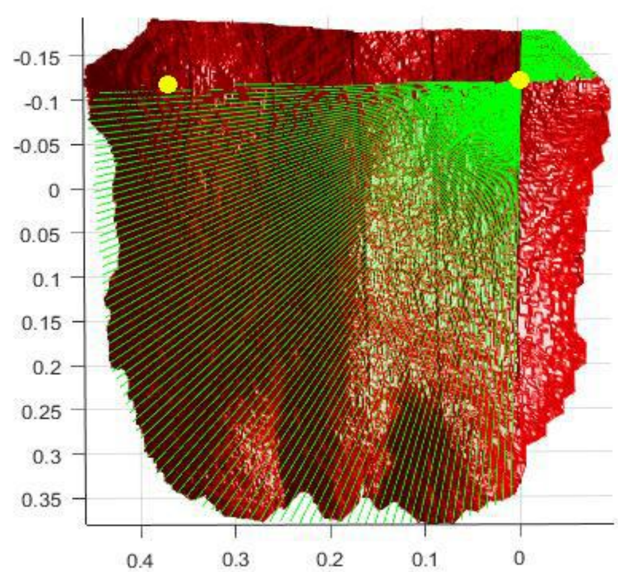
In the next step, the exact position of the bones of the hook was identified. In this section, the Imregionalmax function in Matlab was used to determine the local bumps on the cow body surface.

To extract a feature from the images to be correlated to the BCS it was hypothesised that the local bump and dimples of the surface will disappear when cows get fat. Therefore introducing a consistent ripple factor would reflect the changes in BCS. Ripple factor can be defined as the variation around the trend line of the data. similar to the definition of a coarseness factor (Jafari, Fazayeli, & Zarezadeh, 2014; Jafari, Zarazadeh, & Fazayeli, 2012) ripple factor was defined to express local undulations with the difference that instead of using parallel lines, angular lines were used to include changes in all directions.

**Radial Descriptor Lines (RDL)**

After detecting the hook bones, the connecting line between the hook bones was considered as the benchmark and the origin for drawing the lines with different angles (Fig.1). Radial lines with an angle $\theta$ respect to the connecting line were drawn from the origin of one of the hooks having 1-degree intervals. Because of the symmetry of the cow's body in two sides around the spine, one of the hooks (right hook) sufficed to be considered in the feature extraction.

The projection of each line on the surface of the cow’s back produced a graph which showed the variations of the cow's body surface along the orientation of corresponding RDL.

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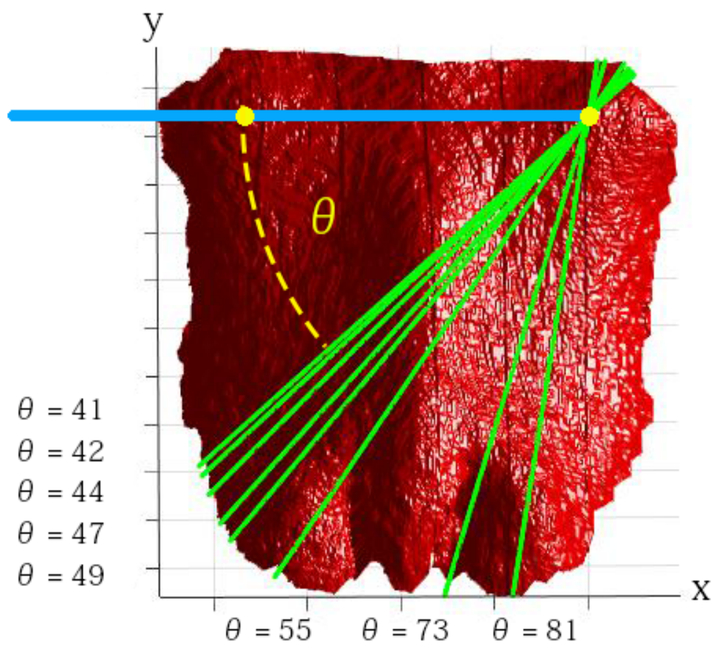


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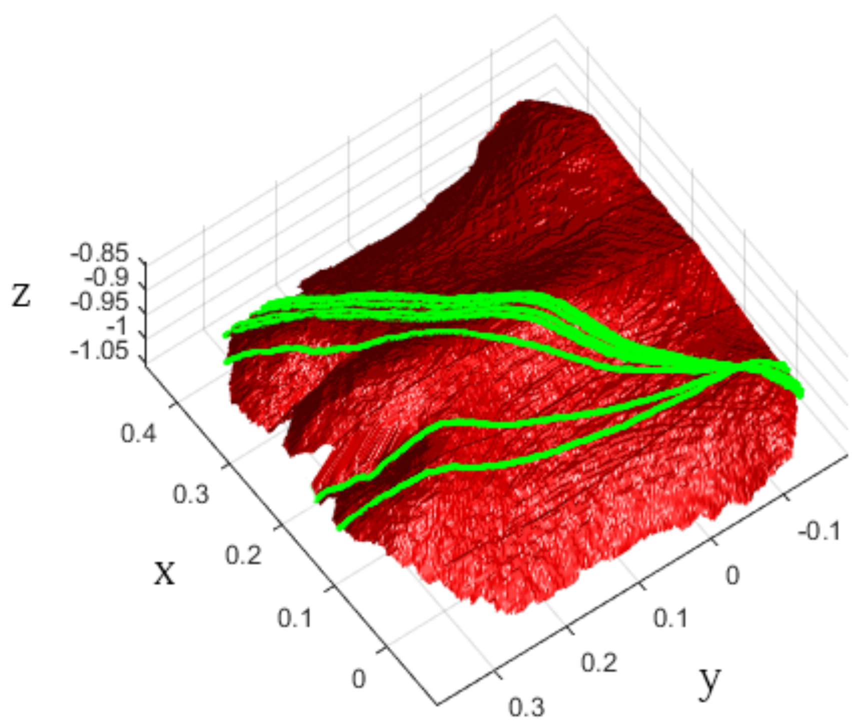


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**Fig.1 a) Radial descriptor lines (RDL) drawn from the origin on the hook pin with 1-degree intervals, b) RDL angle respect to the hooks connecting line c) Projection of the RDLs on cows body surface**

### Ripple Factor

In the next step, a ripple factor was aimed to be extracted from the graphs. To get this ripple factor, we need to consider a datum or comparison line at first.

It should be noted that in this method the datum line was not fixed during the time and would be changed at different body conditions. Also, this method did not directly measure the changes of the mass body respect to a fixed datum line, instead it measured the undulations of the surface. This measure would be then correlated to the BCS at each condition.

Data variance can be used to represent ripples. Since the variance of the data is measured relative to a fixed line (x-axis), if the graph has a slope or curvature, the variance (or measurement of variation relative to a fixed line) is largely due to the difference in overall height of the regions. Therefore, the calculated variance is both due to the general difference (slope or curvature), as well as the small differences (ripples) while we need to measure mere ripples.

But how the general difference could be differentiated from the local differences? In the other words, which order of the polynomial would yield a better result?

By approaching the datum to the graph, the overall height will be eliminated better. But part of the local difference that has been the main goal may also fade.

So excessive approaching the base curve to the main graph can cause the loss of undulation traces. Therefore the question would be the degree which can retain the local ripple information while eliminating overall curvature information.

To find the answer, the optimal level of approaching the base curve to the graph was determined by assessing various curves. Polynomials with different orders from 2 to 5 were fitted on the graphs whereas their comparison would determine the optimum base curve. The criterion for this selection of ripples was their correlation with BCS. The baseline with the highest correlation with BCS would be regarded as the base curve.

On this basis the ripple factor was defined as:

$$Ripple\ Factor = \frac{\sum_{i=X_1}^{X_2} |Z_i - P_i|}{L_D} \qquad (1)$$

Where

Zi: Height of ith point on the cow's skin along the radial line

Pi: Height of ith point on the polynomial fitted curve

L: projected length of the radial line

Higher orders more than five were not assessed since they tend to overfit the graph and thus the corresponding variations would express tiny changes on the surface which are not logically correlated to body condition changes.

Based on the equation (1), the area bounded to the main skin and the base curve was considered as the extracted feature. In order to normalize the measurements, each of the obtained values has been divided by the projected length of the corresponding RDL.

Since the extracted features were obtained from different parts of the back of the cow, each of them could have substantial information. For this reason, to include all information in a comprehensive model and in order to increase the accuracy of the determination, neural network models were developed to determine the BCS.

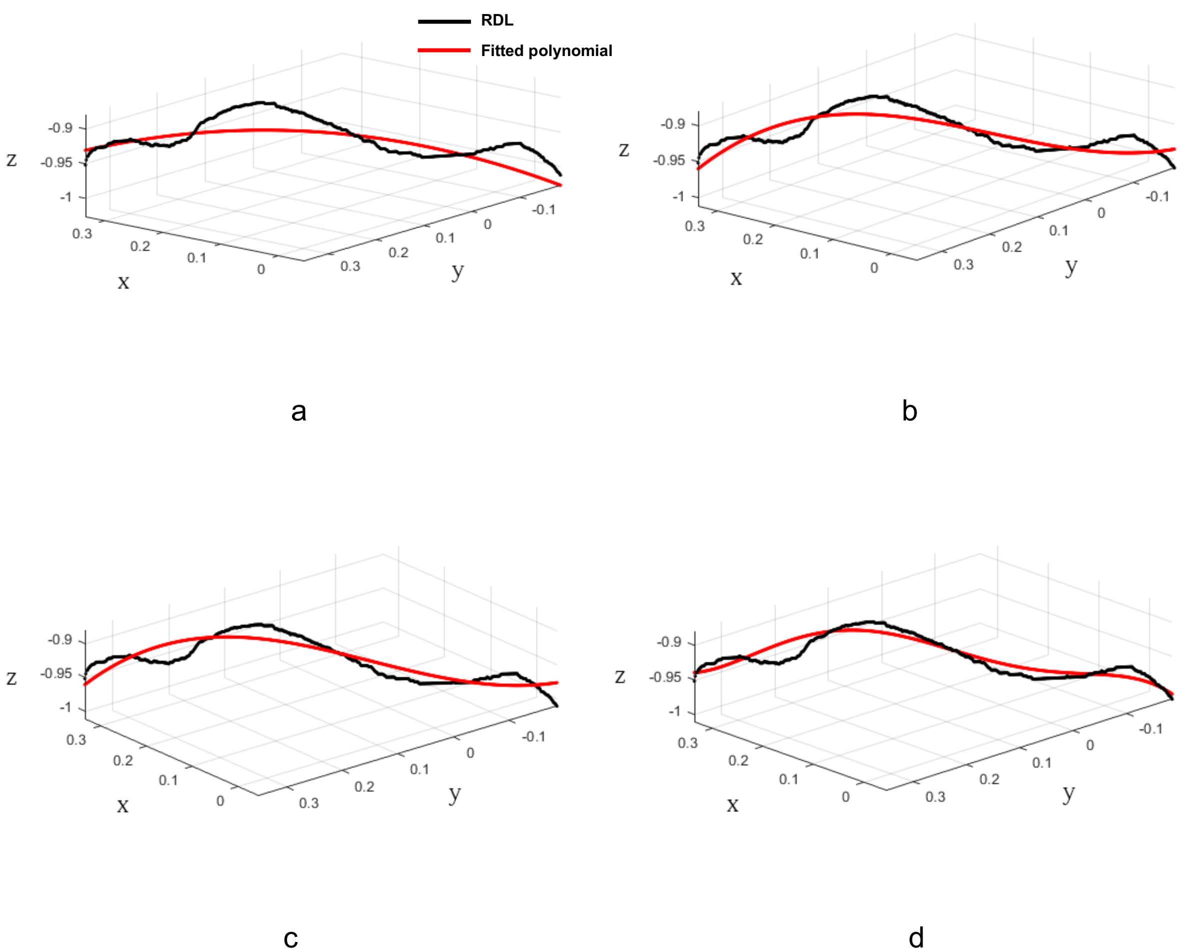


**Fig. 2 Polynomials fitted on RDL at θ = 55° from a cow with BCS 3.5; a) order of 2, b) order of 3, c) order of 4, d) order of 5. The normalized area bounded to these two lines were used in the ripple factor as the extracted feature**

## Results

Taking into account all possible combinations of line angles and polynomials with different orders, a total of 360 (= 4×90) features were extracted.

At first, the correlation between the selected polynomials as a datum with BCS was analysed by investigating a linear correlation between the ripple factors extracted from all the 90 RDLs with BCS. (Table1)

**Table1. The overall correlation between the features extracted from different datum curves and BCS**

| Polynomial Order | 2 | 3 | 4 | 5 |
|---|---|---|---|---|
| Correlation coefficient (R) | 0.906 | 0.947 | 0.925 | 0.923 |

Tables 1 shows that the extracted features have a good correlation with BCS in total while the features based on the polynomial of order 3 had the highest correlation with BCS. However, for the efficient use of these features in a model such as neural network, a determination of the principal components or selection of the most correlated features are needed.

In the next step, the most effective features which had the highest correlation with BCS were determined from the radial descriptor lines in the range of 1-90 degrees and polynomials of orders 2 to 5 were selected by using Best First algorithm in Correlation-based Feature Selection (CFS) method (Table 2).

**Table 2. Effective features extracted from the radial descriptor lines and polynomials selected using CFS**

| Polynomial order | 2 | 3 | 4 | 5 |
|---|---|---|---|---|
| Angle of RDL (degree) | 41,42,44,47,49,55 | 52,55,57,73 | 44,46,49,52,55,73 | 53,56,57,60,81 |

As it can be seen in table 2 the selected set of the lines is different for each polynomial. For example, for the polynomial of order 2, the selected lines lie in the region between 41 to 55 degrees while for the polynomial of order 3 the selected region is between the lines 52 and 73 degrees.

The reason for this can be referred to the number of convexities in that region and its similarity to a specific polynomial. Referring to Fig.1 it can be seen that appearance of one major convexity in the region of spine has made the selected feature to be a quadratic equation for the specified set of RDLs between 41 to 55 degrees.

As the line angle increases, the number of convexities increases in the near-tail region, and therefore a higher-order curve can better be fitted on these surfaces. Since the higher the order of a polynomial the better the fit (Fraden, 2004), the polynomials of order 4 and 5 could also fit a broader range of curvatures comparing to orders 2 and 3.

Another interesting point is that the lines with angles lower than 41 degrees were not selected in any of the classes of polynomials which means no significant variation in the apparent changes in that area occurred as an indication of BCS changes.

Also, the intervals between the selected LDRs show that the resolution of 1 degree was higher than the required amount. Thus, defining the lines with a resolution of 3 degrees may also provide a reasonably good result.

In general, to have a good descriptive feature, two conditions should be satisfied; at first, the described feature should be a good representative of the surface ripples, and secondly changes in the ripples of those regions should be reflective of changes in BCS.

Accordingly, the results in table 2 can be referred to these two reasons. This is the reason that in spite of the significant changes occur in the accumulated mass in the region between 81o to 90o when BCS changes, the smoothness of the surface does not change that much to be a good representative of BCS.

To determine the consistency of the correlation between the extracted features and BCS, the performance of the features were compared for both training and test sets (Table 3).

**Table 3. The best performances of neural networks trained with features corresponding to each polynomial**

| Features | R2 | MSE | MAE |
|---|---|---|---|
| Training set (n = 99) | | | |
| Poly2-CFS Features | 0.66 | 0.078 | 0.207 |
| Poly3-CFS Features | 0.82 | 0.037 | 0.159 |
| Poly4-CFS Features | 0.77 | 0.048 | 0.178 |
| Poly5- CFS Features | 0.66 | 0.078 | 0.221 |
| Test set (n = 33) | | | |
| Poly2- CFS Features | 0.61 | 0.107 | 0.215 |
| Poly3- CFS Features | 0.75 | 0.063 | 0.213 |

| | | | |
|---|---|---|---|
| Poly4- CFS Features | 0.66 | 0.075 | 0.209 |
| Poly5- CFS Features | 0.60 | 0.098 | 0.249 |

MLP neural networks with one and two hidden layers were developed as a model for prediction of BCS. The inputs consist of ripple factors extracted from the RDLs. The topology of the ANNs varied in the number of neurons in the hidden layer whereas one and two hidden layer networks were tried.

To train the network, 165 images of 55 cows were randomly divided into three sets: 60% for training (n = 99), 20% for validation (n = 33) and 20% for network testing (n = 33).

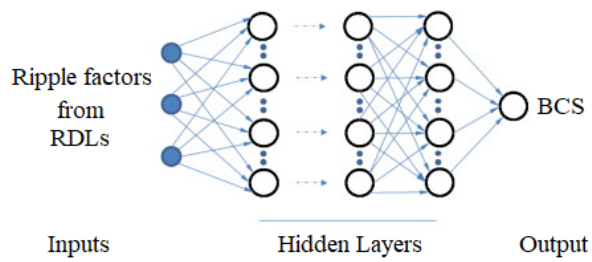


**Fig. 3 Schematic of the neural network used for BCS determination based on the features extracted from RDLs**

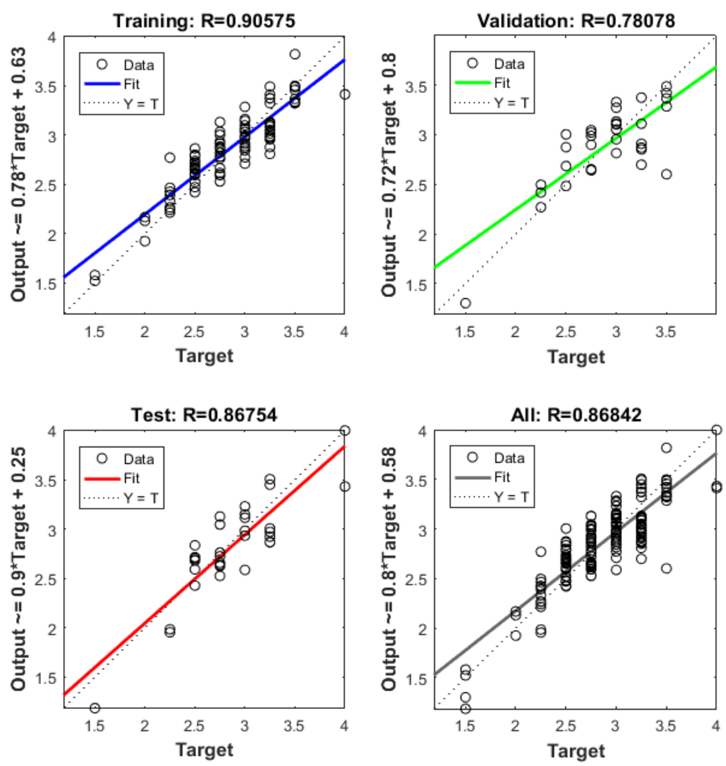


**Fig4. Estimation of BCS based on ripple factors extracted from RDLs by means of ANN**

The best performance was observed from the network with 30 and 5 neurons in the hidden layers respectively. The network was save for further analysis where a comparison between its output and the values of BC scored by the experts showed a good agreement between these two (Fig.4)

The results were evaluated based on the coefficient of determination (R2), and root mean squared error (MSE)

## Conclusion

The region at the cow's back between hook and pin bones is one of the main regions that significantly reflects the body condition score (BCS). In this study, BCS-related features were extracted throughout this region from every direction with high resolutions by exploiting radial descriptor lines (RDL).

Ripple factor was defined as a measure of undulation of cow's body surface and was extracted from the RDLs. Results showed that undulations along of the RDLs between 41 to 81 degrees can be a good representative of the cow's BCS

As the second variable in the ripple factor definition, the similarity of the undulation curve to a specific polynomial could affect the extracted feature (ripple factor). Investigating several orders of the polynomials demonstrated that a unique polynomial should not be used as the base curve since the convexities in different regions vary.

Results showed that there is a good agreement between some of the RDL ripple factors and BCS whereas a combination of all the features could be effectively utilized by a neural network for BCS estimation with a correlation up to 0.86 and MSE of 0.036 for test data.

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