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CHIU, Chuang-Yuan, CIEMS, Raimonds, THELWELL, Michael <http://orcid.org/0000-0003-0145-0452>, BULLAS, Alice <http://orcid.org/0000-0003-2857-4236> and CHOPPIN, Simon <http://orcid.org/0000-0003-2111-7710>

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Estimating somatotype from a single-camera 3D body scanning system

Chuang-Yuan Chiu [a], Raimonds Ciems[b], Michael Thelwell[a], Alice Bullas[a] and Simon Choppin[a]

[a]Sports Engineering Research Group, Sheffield Hallam University, Sheffield, UK; [b]Hawk-eye Innovations Ltd., Basingstoke, UK

ABSTRACT

Somatotype is an approach to quantify body physique (shape and body composition). Somatotyping by manual measurement (the anthropometric method) or visual rating (the photoscopic method) needs technical expertize to minimize intra- and inter-observer errors. This study aims to develop machine learning models which enable automatic estimation of Heath-Carter somatotypes using a single-camera 3D scanning system. Single-camera 3D scanning was used to obtain 3D imaging data and computer vision techniques to extract features of body shape. Machine learning models were developed to predict participants' somatotypes from the extracted shape features. These predicted somatotypes were compared against manual measurement procedures. Data were collected from 46 participants and used as the training/validation set for model developing, whilst data collected from 17 participants were used as the test set for model evaluation. Evaluation tests showed that the 3D scanning methods enable accurate (mean error < 0.5; intraclass correlation coefficients >0.8) and precise (test-retest root mean square error < 0.5; intraclass correlation coefficients >0.8) somatotype predictions. This study shows that the 3D scanning methods could be used as an alternative to traditional somatotyping approaches after the current models improve with the large datasets.

KEYWORDS
3D analysis; body composition; measurement; modeling; technology

1. Introduction

Somatotype is an approach to quantify body physique (shape and body composition) (Hume & Ackland, 2017). It was originally developed in an attempt to relate body physique with intelligence, moral worth and future achievement, though this idea that body type is an indicator of temperament has since been disputed (Carter, Carter, & Heath, 1990; Sheldon, 1954; Sheldon, Stevens, & Tucker, 1940; Vertinsky, 2007). However, somatotyping is now widely used, particularly the Heath-Carter revision of the method which represents body shapes along three scales based on manual measurement (the anthropometric method) or visual photoscopic ratings (the photoscopic method), in an attempt to relate body physique and sports characteristics (Carter et al., 1990; Olds, Daniell, Petkov, & David Stewart, 2013).

Carter, Ackland, Kerr, and Stapff (2005) and Martín-Matillas et al. (2014) indicated that individuals' somatotype is related to their playing positions in team sports. Moss, McWhannell, Michalsik, and Twist (2015) and Bacciotti, Baxter-Jones, Gaya, and Maia (2018) compared different level athletes' somatotype and found that elite-level handball players tend to have central somatotype class, while sub-elite gymnasts have significantly higher mesomorph components compared to recreational gymnasts. This suggests that elite performers in a particular sport tend to have different body type characteristics compared to the general population. Ryan-Stewart, Faulkner, and Jobson (2018) and Giannopoulos, Vagenas, Noutsos, Barzouka, and Bergeles (2017) showed that somatotype can even be related to specific sports performance attributes, such as attacking performance in volleyball and anaerobic performance (e.g. 3 repetition maximum bench press and back squat). Consequently, previous literature has suggested somatotype has the potential to be used in a variety of applications, such as sports talent identification and development (Buśko, Lewandowska, Lipińska, Michalski, & Pastuszak, 2013; Milić et al., 2017).

The equipment used in both manual measurement and visual rating procedures is easily accessible and simple to calibrate. Consequently, the use of manual measurement tools is prevalent within applied sports practice and research, with both national and international databases of these measures currently available (Hume, Sheerin, & de Ridder, 2018). Nevertheless, manual measurement and visual ratings need technical

CONTACT Chuang-Yuan Chiu c.chiu@shu.ac.uk Advanced Wellbeing Research Centre, Sheffield Hallam University, Olympic Legacy Park, 2 Old Hall Road, Sheffield, S9 3TU, UK

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expertize to minimize intra- and inter-observer errors, with photoscopic somatotype only able to be rated objectively by those who have had validity and reliability established against those of an experienced criterion (Hume & Marfell-Jones, 2008; Perini, de Oliveira, Ornellas, & de Oliveira, 2005).

In an attempt to overcome the requirement of technical expertize, previous studies have explored alternative techniques for obtaining the Heath-Carter somatotypes. Anisimova, Godina, Nikolaev, and Rudnev (2016) used bioelectrical impedance analysis (BIA) and regression models to predict endomorph and mesomorph scales. Olds et al. (2013) applied 3D scanning techniques to extract anthropometrics, including segment lengths, breadths, girths, and volumes to characterize somatotype clusters using machine learning techniques. However, both attempts cannot estimate the exact values of all three Heath-Carter scales. No model has previously been developed to estimate ectomorph scales from BIA. The method developed by Olds et al. (2013) can only indicate specific clusters instead of the real values (numbers) of all three Heath-Carter scales.

Recently, novel 3D reconstruction techniques that use low-cost depth cameras to generate 3D human models have become commercially available – increasing the accessibility of 3D scanning (Newcombe et al., 2011). The suitability of these systems is further encouraged by reports with acceptable accuracy in 3D reconstruction, for example, Chiu et al. (2019) indicated that the difference between the models produced by 3D reconstruction and commercial 3D scanning system were less than 1 cm. Some commercial solutions have also developed automatic body measurement techniques, which extract anthropometric data without the need for technical expertize for manual data post-processing (Ng, Hinton, Fan, Kanaya, & Shepherd, 2016). Wong et al. (2019) used these techniques to obtain anthropometrics and estimated body composition by machine learning models. The accessibility of this technology facilitates the extraction of measures beyond conventional anthropometric data (segmental length, breadth, girth, surface area, and volume), such as principal components of 3D body shape variation; which can complement existing anthropometric measures in estimating blood metabolites, body composition, and functional strength (Ng et al., 2019). By using principal components, a more accurate prediction of these factors is achievable than simply using conventional anthropometrics (Ng et al., 2019). To the best of the authors' knowledge, no model has been built to estimate all three scales in Heath-Carter somatotype using 3D scanning techniques. Thus, this study aims to develop machine learning models, which enable the estimation of Heath-Carter somatotypes from the principal components of body shape variation, using a single-camera 3D scanning system.

2. Material and methods

2.1. Participants

The study received institutional ethical approval before commencing. All tests were conducted in the labs at the university campus with a comfortable temperature. Volunteers who are age above 18, able-bodied (people without amputations or missing limbs), not pregnant were invited to participate in this study. Sixty-three participants were recruited in this study and all participants provided written consent before participating. Participants were separated into two groups: training/validation set ($n = 46$ participants) for model development; test set ($n = 17$ participants) for model evaluation. Participants' characteristics are listed in Table 1. Each participant was measured using traditional manual anthropometric techniques and had 3D scan data captured using a single-camera 3D scanning system (Chiu et al., 2019). All participants were requested to wear non-compressive form-fitting shorts, with female participants also required to wear a form fitting, non-compressive sports top during data collection.

2.2. Traditional manual measurement

Anthropometric data collected from participants included: Stature, Mass, Skinfolds of Triceps, Subscapular, Supraspinale, Medial Calf, Girths of Bicep (flexed and tensed) and Calf, as well as Bone Breadths of Humerus

Table 1. Participants' characteristics for the train/validation and test group.

	Train / Validation Group	Test Group	All
Number of participants	34 males, 12 females	12 males, 5 females	46 males, 17 females
Trial number	138 trials	34 trials	172 trials
Age (years)	30 ± 11 (18, 61)	28 ± 10 (19, 57)	29 ± 11 (18, 61)
Body mass (kg)	75.9 ± 17.4 (50.9, 139.4)	76.6 ± 12.6 (56.9, 105.9)	76.1 ± 16.2 (50.9, 139.4)
Body height (cm)	176.7 ± 9.5 (156.3, 193.5)	176.0 ± 6.8 (165.6, 187.2)	176.5 ± 8.8 (156.3, 193.5)
Endomorphy (manual)	3.0 ± 1.3 (1.0, 6.6)	3.4 ± 1.4 (1.8, 7.1)	3.1 ± 1.3 (1.0, 7.1)
Mesomorphy (manual)	5.1 ± 1.5 (2.0, 8.9)	5.1 ± 1.8 (2.3, 9.5)	5.1 ± 1.5 (2.0, 9.5)
Ectomorphy (manual)	2.3 ± 1.4 (0.1, 5.3)	2.1 ± 1.2 (0.1, 4.6)	2.2 ± 1.3 (0.1, 5.3)
Endomorphy (3D scan)	2.9 ± 1.1 (0.8, 5.4)	3.2 ± 1.3 (1.5, 6.0)	3.0 ± 1.1 (0.8, 6.0)
Mesomorphy (3D scan)	5.1 ± 1.2 (2.7, 8.6)	5.2 ± 1.3 (3.0, 7.7)	5.1 ± 1.2 (2.7, 8.6)
Ectomorphy (3D scan)	2.3 ± 1.3 (−0.2, 4.8)	1.8 ± 1.3 (−1.4, 3.6)	2.2 ± 1.3 (−1.4, 4.8)

Minimum and maximum values for characteristics were listed in the brackets.

and Femur. All manual measures were collected by an accredited anthropometrist (ISAK level 1 or 2), according to standard protocols and equipment of the International Society for the Advancement of Kinanthropometry (Stewart, Marfell-Jones, Olds, & De Ridder, 2011). The Heath-Carter somatotypes were calculated within Excel (Microsoft, USA). The Heath-Carter somatotype obtained by the traditional manual measurement was used as a reference scale for model development and evaluation.

2.3. Test procedures with a single-camera 3D scanning system

The single-camera 3D scanning system (Chiu et al., 2019) was used to obtain 3D data. This single-camera 3D scanning system consisted of a Microsoft Kinect V2 mounted on a rotating camera rig with a central-stationary platform to capture participants' depth images from different directions. The Microsoft Kinect V2 was mounted at a height between 0.8 and 1.0 metres and a capture distance between 1.4 and 1.7 metres. The height and capture distance were adjusted according to each participants' stature to enable their full-body depth images to be captured. KinectFusion techniques (Newcombe et al., 2011) were applied to complete the 3D reconstruction and generate 3D point clouds from the captured depth images (Figure 1a). For participants in the training/validation set, three repeated scanning trials were applied so we can have more data points for developing effective model with less bias and variance of error (Brain & Webb, 2000). For participants in the test set, two repeated scanning trials were applied.

2.4. Post-processing for 3D data

The random sample consensus (Fischler & Bolles, 1981) and distance filters were applied to remove noise on the 3D point clouds obtained from the scanning system, such as the floor, scanning platform, or reflections (Figure 1b). The Screened Poisson Surface Reconstruction (Kazhdan & Hoppe, 2013) in Open3D library (Zhou, Park, & Koltun, 2018) were then used to generate the individual 3D human model as shown in Figure 1c.

The generated individual 3D human models were matched by the deformable model, "skinned multi-person linear model" (Loper, Mahmood, Romero, Pons-Moll, & Black, 2015) as shown in Figure 1d and e.

The correspondence between the reconstructed 3D human models and skinned multi-person linear base models were acquired by 3D-CODED (Groueix, Fisher, Kim, Russell, & Aubry, 2018). The optimization techniques, "BOBYQA" (Powell, 2009), via the software package, NLopt (Johnson, 2020), was used to adjust pose and shape parameters (i.e. the principal components) to minimize differences between deformable models and their correspondence. The adjusted shape parameters (the principal components of body shape) were regarded as the extracted features for estimating somatotypes.

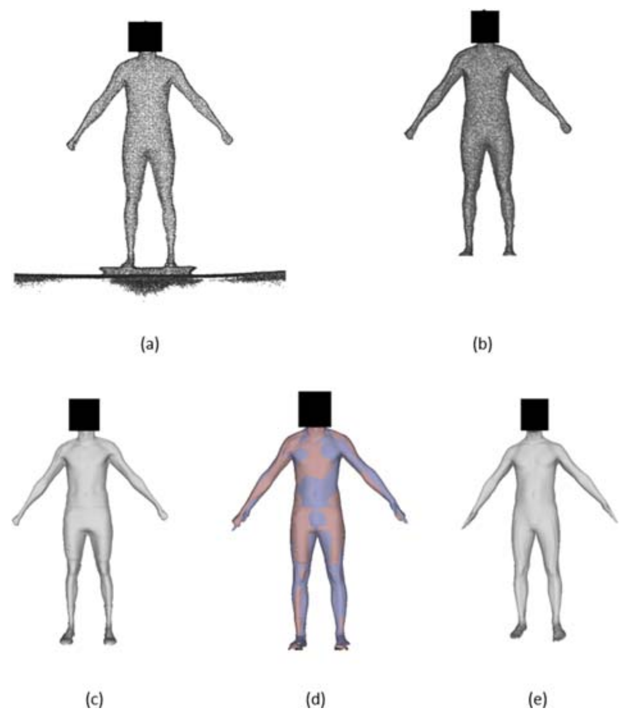

Figure 1. Overview of post-processing for 3D data in this study. (a) a 3D point cloud obtained from the single-camera 3D scanning system. (b) a 3D point cloud after removing noise. (c) a reconstructed mesh from the filtered 3D point cloud. (d) a deformed skinned multi-person linear model (blue) that fit the reconstructed mesh (red). (e) a deformed skinned multi-person linear model.

2.5. Model development

LIBSVM (Chang & Lin, 2011) was used to find three regression models for estimating the scales of the Heath-Carter somatotype (i.e. ectomorphy, endomorphy, and mesomorphy). The shape features (the shape parameters of the deformable skinned multi-person linear model) and gender were used as the inputs of the model. The values of the three somatotype scales were regarded as the output of each model. The data collected from the training/validation set were used to train the weight and the bias of the LIBSVM regression models. Randomized parameter optimization was applied to find the best non-trainable parameter setting of the support vector regressors.

2.6. Evaluation tests

The developed models which were built with optimized weight, bias and nontrainable parameters were then applied to estimate the somatotypes of the participants in the test set. Each participant's gender with two sets of shape features obtained from repeated trials were used to estimate two sets of somatotypes. In total, 34 sets of somatotypes estimated from 17 participants in the test group were obtained. Each participant's mean somatotype scales estimated from the 3D scan was compared with a reference set of somatotype obtained from traditional manual measurement. Bland–Altman analysis, standard errors, intraclass correlation coefficients (ICC), standardized mean difference and the coefficient of variation (CV) were calculated to determine the accuracy of the proposed methods. The test-retest precisions of repeated trials from the test set were also calculated by comparing the estimated somatotypes of repeated trials and quantified by root mean square errors, ICC, standardized mean difference and the CV.

3. Results

Participants' measured and predicted somatotypes are shown on standard somatocharts (Figure 2a and b). The intra-observer relative technical error of measurement for all three anthropometrists was less than 5% in skinfolds and 1% in all other measurements, shown in Supplemental Table 1. Mesomorphy (manual measurement result: 5.1 ± 1.5) was the dominate component for the participants in this study. The results of the evaluation tests are shown in Table 2.

For all participants in the test group, the mean errors for all three components were less than 0.5. The root mean square error of repeated measures was less than 0.5 for all components. The ICC for both accuracy and reliability were higher than 0.8 for all participants in the test group. Compared with mesomorphy and ectomorphy, the model estimated endomorphy with a larger 95 % limits of agreement for the test groups with all participants.

The developed models show differences in performance for male and female participants. The developed models generate large bias (absolute mean error) for female ectomorph and mesomorph components. The developed model tends to underestimate endomorph scales for male participants but shows the opposite trend for female endomorph scales. The root mean square error of males is less than that of females. The ICC for the accuracy of female endomorph scales were less than for males. The calculated CV for reliability of male ectomorphy was higher than for females.

Most absolute values of standardized mean differences for both accuracy and reliability were less than 0.2. The CV for mesomorph accuracy (9.14%) was smaller than for endomorph and ectomorph accuracy (17.66% and 11.68%). A similar trend was also shown in the CV for reliability. The CV for mesomorph reliability were less than 5%, while CV for endomorph and ectomorph were usually larger than 5%.

4. Discussion

The aim of this study was to develop machine learning models which enable estimation of Heath-Carter somatotypes from principal components of body shape variation, using a single-camera 3D scanning system. By

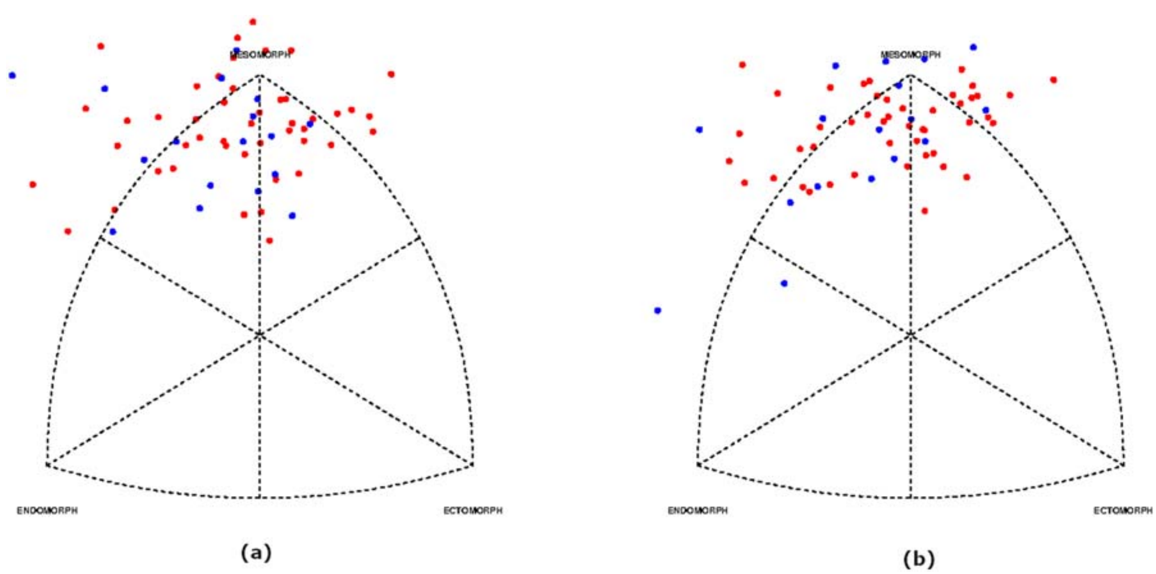

Figure 2. Test results in this study. Somatochart for the participants obtained from (a) manual anthropometry and (b) 3D scan (the mean prediction for each participant) of this study. (Red: Train/Validation set; Blue: Test set).

Table 2. Results of the evaluation tests which compared the manual measurement and the prediction from 3D scanning.

All Participants in Test Group ($n = 17$)										
	M±S	LoA	SSE	ICC-a	SME-a	CV-a	RMSE	ICC-r	SME-r	CV-r
Endomorphy	−0.20 ± 1.06	−2.28, 1.88	0.26	0.82	−0.15	17.66 %	0.28	0.98	0.01	5.81 %
Mesomorphy	0.11 ± 0.77	−1.39, 1.62	0.19	0.94	0.07	9.14 %	0.25	0.98	−0.08	2.75 %
Ectomorphy	−0.20 ± 0.63	−1.43, 1.02	0.15	0.93	−0.17	11.68 %	0.19	0.99	0.04	20.14 %
Male Participants in Test Group ($n = 12$)										
	M±S	LoA	SSE	ICC-a	SME-a	CV-a	RMSE	ICC-r	SME-r	CV-r
Endomorphy	−0.52 ± 0.81	−2.11, 1.07	0.23	0.91	−0.37	18.81 %	0.24	0.98	−0.02	6.31 %
Mesomorphy	−0.05 ± 0.82	−1.65, 1.56	0.24	0.92	−0.03	8.01 %	0.21	0.99	−0.11	2.00 %
Ectomorphy	−0.05 ± 0.61	−1.25, 1.15	0.18	0.94	−0.04	8.69 %	0.17	0.99	0.05	25.34 %
Female Participants in Test Group ($n = 5$)										
	M±S	LoA	SSE	ICC-a	SME-a	CV-a	RMSE	ICC-r	SME-r	CV-r
Endomorphy	0.56 ± 1.29	−1.98, 3.10	0.58	0.55	0.48	14.88 %	0.35	0.95	0.09	4.61 %
Mesomorphy	0.49 ± 0.51	−0.51, 1.49	0.23	0.89	0.61	11.85 %	0.33	0.90	−0.04	4.54 %
Ectomorphy	−0.57 ± 0.55	−1.64, 0.51	0.25	0.93	−0.52	18.86 %	0.25	0.99	−0.01	7.64 %

M±S: mean ± standard deviation of error, LoA: 95% limit of agreement, SSE: standard error, ICC-a: intraclass correlation coefficient for accuracy, SME-a: standardized mean difference for accuracy, CV-a: coefficient of variation for accuracy, RMSE: root mean square error, ICC-r: intraclass correlation coefficient for reliability, SME-r: standardized mean difference for reliability, CV-r: coefficient of variation for reliability.

using 3D scanning techniques, technical expertize for traditional manual measurement and visual rating could be avoided. The proposed methods perform automatic post-processing of acquired 3D scan data, minimizing the requirement of expertize necessary in previous clustering approaches (Olds et al., 2013). Unlike clustering approaches (Olds et al., 2013), the proposed method estimated the real values for each of the somatotype scales, providing further information for body measurement and monitoring. The proposed methods avoid the necessity for invasive body contact during manual measurement and body landmarking procedures used in previous 3D scanning techniques (Olds et al., 2013). The developed algorithms can be also applied to the data from commercial 3D scanning systems.

The evaluation results show that the proposed models can estimate somatotype with small mean error (<0.5) and high ICC for accuracy (> 0.8). The standard errors of the proposed methods (< 0.3) were much less compared to the errors produced by BIA (>0.5; Anisimova et al. (2016)). Furthermore, the proposed method can estimate ectomorph scales, which cannot be estimated from the approaches developed by Anisimova et al. (2016). Thus, the proposed method provides an alternative to traditional manual and visual rating approaches of somatotyping, compared to BIA. The proposed methods were shown to be able to determine somatotypes and combine previous research for sports performance prediction (e. g. anaerobic performance), sports talent identification and development.

The 95 % limit of agreement and the CV were larger for predicted endomorphy compared to ectomorphy and mesomorphy which suggests that the proposed models demonstrate differences in accuracy in the prediction of each of the three somatotype components. This is potentially attributable to the difference between the endomorphy distribution of the training/validation group (3.0 ± 1.3) to that of the test group (3.4 ± 1.4). The difference in endomorphy was larger than the other components. This difference might also cause a large bias for the male and female endomorphy (absolute mean error > 0.5). The participants in this study were classified predominantly within the mesomorph region of the somatochart, meaning that there was less variation in body types and compositions to train the regression models (Figure 2a and b). Similarly, the reduced number of female participants might have caused a larger bias (absolute mean errors) than for male participants. Because the models trained with both male and female participants, the bias for male and female group show opposite directions (e. g. underestimation for male endomorph and overestimation for female endomorph). Less female participants might lead to a large bias in mesomorph and ectomorph scales. Further studies should be conducted to collect data from a large cohort of male and female participants with a wider range of body type characteristics and somatotypes for retraining and testing of the proposed models, to improve the estimation accuracy of an individual's somatotype in all three components.

The proposed method avoids using BIA to extract features. Moreover, using parametric models (skinned multiperson linear model) to fit the scanning data to avoid the pose variations and extract "pose-invariant" features (Hume & Ackland, 2017). These minimized the effect of noise (e.g. differences in posture between repeated trials) and lead to good levels of precision of the proposed method (RMSE < 0.5, the ICC for reliability > 0.9). Ng et al. (2019) also showed that using similar techniques for 3D data capturing and processing could estimate other characteristics (e.g. body composition) reliably. However, the difference in repeated trials still exists because of the random errors generated from the process of depth image capturing and feature extraction. In addition, this caused large test-retest error for participants with extreme body types (e. g. ectomorph scales were close to 0 in the male test group), leading to high CV of reliability in male ectomorphy. Further studies should be conducted to improve the quality of depth camera data, the robustness of feature extraction for estimation of somatotype, as well as the estimation of more useful body characteristics for use in sports sciences (e. g. body composition) from 3D scanning data.

Three anthropometrists contributed to the collection of body measurements in this study to improve the efficiency of data collection. All three anthropometrists were found to meet the requirements for intra-observer reliability according to ISAK. The models might estimate the somatotypes with less personal effect than the ones generated by a single measurer. Although ISAK level 1 & 2 anthropometrists improve the accuracy and reliability of manual measurement (Perini et al., 2005), the intra- and inter-observer technical error of measurement (TEM) potentially still affects the model development and analysis results. Inviting an ISAK level 3 or 4 anthropometrist to control the quality of data collection is highly recommended for future studies conducting model improvement and validation.

The main limitation of this study is the participants' cohort. Although mesomorphy was the dominate component for participants in this study, this could reflect typical scenarios within sports science applications. However, this means that the developed models were not able to achieve consistent performance when estimating ectomorph or endomorph participants and cause the difference in CV for accuracy and reliability. As a result, the current model might not be appropriate for use in other applications, such as health sciences, where individuals display a greater range of body types. The unbalanced gender ratios in this study led the developed models to demonstrate differences in accuracy and reliability for male and female participants. The small number of participants also led to low standardized mean differences. To the best of the authors' knowledge, this study is the first study to estimate Heath-Carter somatotype scales from 3D scan data with machine learning models. Further study should increase the number of participants in both genders with various somatotypes and train the gender-specific models to enhance prediction performance with non-mesomorph groups and minimize the gender differences.

5. Conclusion

This study developed machine learning models which enable estimation of Heath-Carter somatotypes from principal components of body shapes extracted using a single-camera 3D scanning system. The developed method minimizes the requirement of technical expertize and provides good levels of accuracy and precision compared to other estimation methods. Further study should be conducted to improve the current model with a larger dataset in order to develop an effective alternative to traditional somatotype approaches (manual measurement or visual rating). The proposed method, after improving accuracy and reliability of somatotyping could be used for sports performance prediction (e. g. anaerobic performance), sports talent identification and development and could also be extended to predict additional characteristics, such as body composition.

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ORCID

Chuang-Yuan Chiu http://orcid.org/0000-0002-6512-0084

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