Multidimensional scaling for determining the effect of occupation on entheseal changes

Conference Paper · September 2017

CITATIONS
0

READS
35

1 author:

Charlotte Yvette Henderson
University of Coimbra
69 PUBLICATIONS **466** CITATIONS

SEE PROFILE

BABAO Annual Meeting, Liverpool 8-10 Sept. 2017

Multidimensional scaling for determining the effect of occupation on entheseal changes

Charlotte Henderson

CIAS – Research Centre for Anthropology and Health, Department of Life Sciences, University of Coimbra, Portugal. c.y.henderson@uc.pt

1. Introduction

Aim To use a multidimensional scaling model to determine whether entheseal changes can be used to identify occupation.

Why? Entheseal changes (ECs) (Fig. 1) have been used to study activity, to understand social divisions of labour (Jurmain et al., 2012).

Problems 1. Each change has a different aetiology (Henderson et al., 2017; Villotte et al., 2016)

2. Ageing is associated with a higher frequency of some ECs (Henderson et al., 2013, 2017).

3. Occupation and biomechanics have weaker links with ECs (Alves Cardoso & Henderson, 2013; Michopoulou et al., 2015).

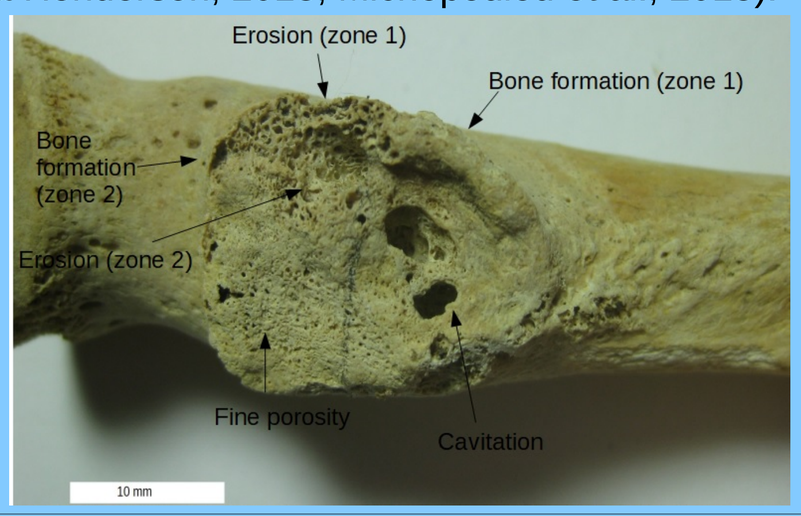


Fig. 1 Some of the features scored in the new Coimbra method

2. Materials & Methods

Materials: Males aged 15+ from Coimbra identified collection without injury or entheseal pathology (n=213) (Henderson et al., 2017)

Methods: 1. New coimbra method for scoring entheses applied to 5 entheses: supra- and infraspinatus insertion, subscapularis insertion, common extensor and flexor origins, and biceps brachii insertion.

2a. Occupations categorised: heavy manual, manual, nonmanual and soldier (Villotte et al., 2010; Alves Cardoso & Henderson, 2013).

2b. Occupations categorised: heavy manual and "ordinary" (pooling of other categories)

Disadvantage of method: There are 5 * 8 variables per side and individual (= 80 variables per individual).

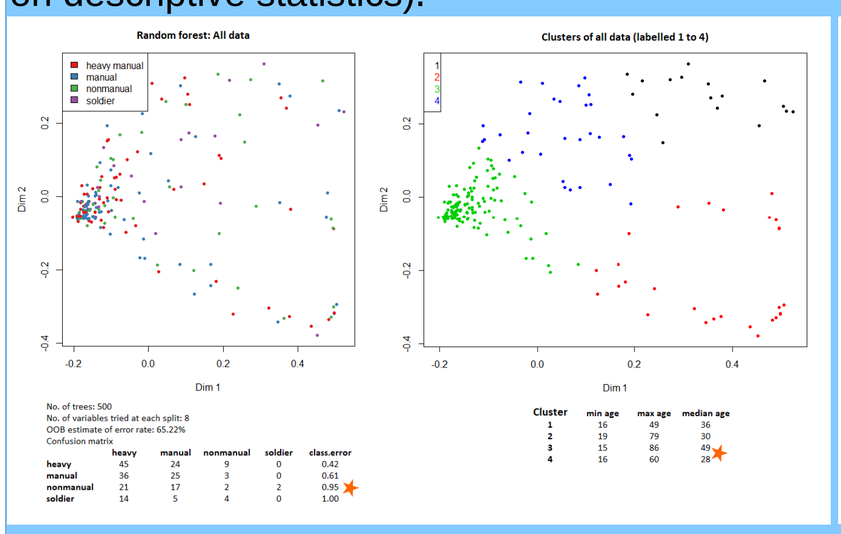
Data reduction: 1 Side symmetry: Right score minus left score = 40 variables per individuals.

2. Agonists: difference in score between muscles "opposing" each other: supra- and infraspinatus score minus subscapularis score. Common extensor score minus common flexor score = 32 variables

3. Random forests used to partition data (raw, asymmetry and agonists) using a supervised model (occupation categories) in R version 3.3.2 using the package "randomForest" (Liaw & Wiener., 2015).

3. Results

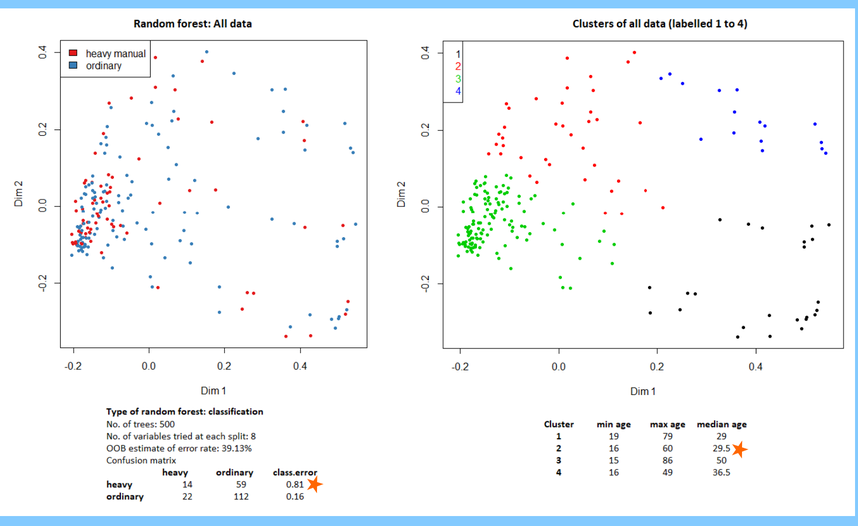
Fig. 2 & 3. Random forest models for the raw data (80 variables) shows poor prediction of occupation category (whether using 4 or 2 categories). Clustering may be more age related (based on descriptive statistics).



No. of trees: 500
No. of variables tried at each split: 8
OOB estimate of error rate: 65.22%
Confusion matrix

	heavy	manual	nonmanual	soldier	class.error
heavy	45	24	9	0	0.42
manual	36	25	3	0	0.61
nonmanual	21	17	2	2	0.95
soldier	14	5	4	0	1.00

Cluster	min age	max age	median age
1	16	49	36
2	19	79	30
3	15	86	49
4	16	60	28

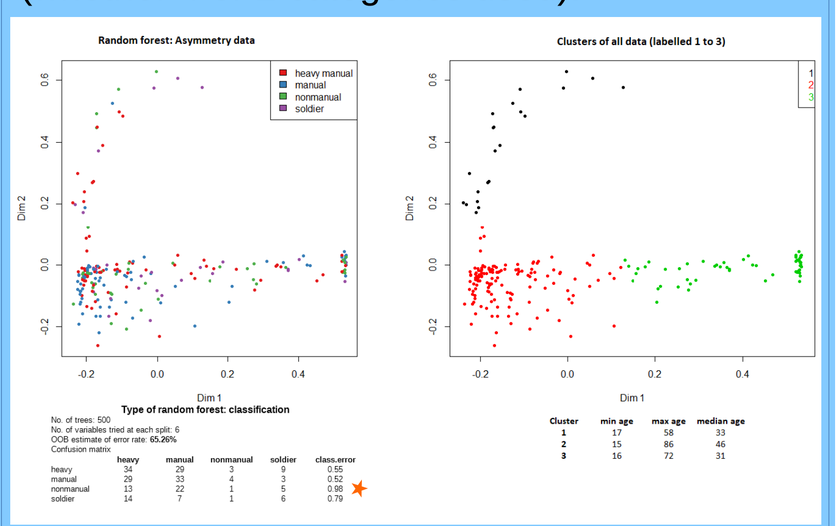


Type of random forest: classification
No. of trees: 500
No. of variables tried at each split: 8
OOB estimate of error rate: 39.13%
Confusion matrix

	heavy	ordinary	class.error
heavy	14	59	0.81
ordinary	22	112	0.16

Cluster	min age	max age	median age
1	19	79	29
2	16	60	29.5
3	15	86	50
4	16	49	36.5

Fig. 4. Random forest models asymmetry data: poor prediction of occupation category (whether 4 or 2 categories used).

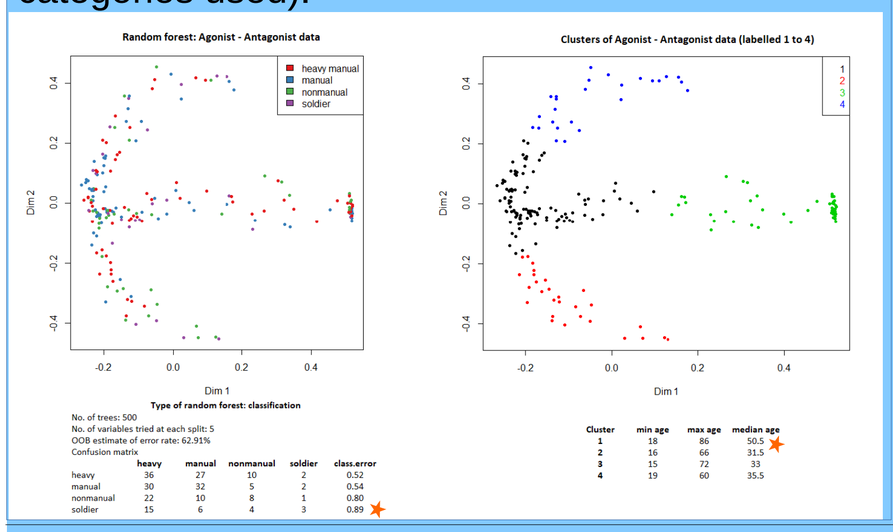


Type of random forest: classification
No. of trees: 500
No. of variables tried at each split: 6
OOB estimate of error rate: 65.26%
Confusion matrix

	heavy	manual	nonmanual	soldier	class.error
heavy	34	29	3	9	0.55
manual	29	33	4	3	0.52
nonmanual	13	22	1	5	0.98
soldier	14	7	1	6	0.79

Cluster	min age	max age	median age
1	17	58	33
2	15	86	46
3	16	72	31

Fig. 5. Random forest models agonist data: poor prediction of occupation category (whether 4 or 2 categories used).

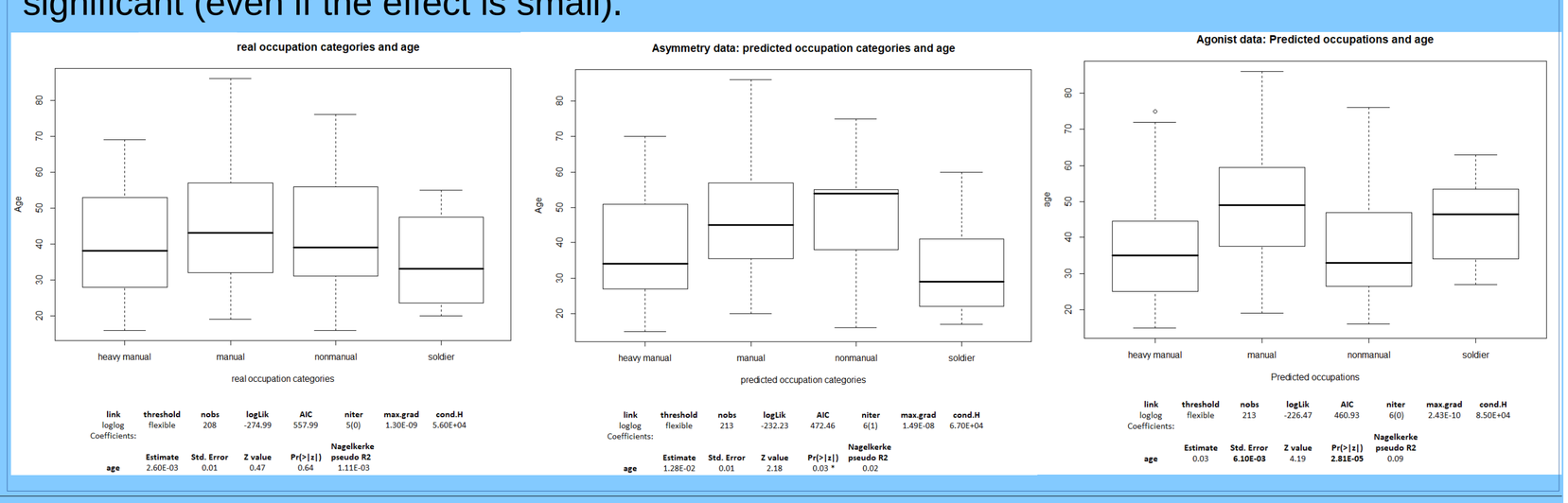


Type of random forest: classification
No. of trees: 500
No. of variables tried at each split: 5
OOB estimate of error rate: 62.91%
Confusion matrix

	heavy	manual	nonmanual	soldier	class.error
heavy	36	27	10	2	0.52
manual	30	32	5	2	0.54
nonmanual	22	10	8	1	0.80
soldier	15	6	4	3	0.89

Cluster	min age	max age	median age
1	18	86	50.5
2	16	66	31.5
3	15	72	33
4	19	60	35.5

Fig. 6 – 8. Boxplots show that the predicted occupation category has a different age structure to the original data. Ordinal regression shows that age differences are significant (even if the effect is small).



	link	threshold	nobs	logLik	AIC	niter	max.grad	cond.H
loglog Coefficients:		flexible	208	-274.99	557.99	5(0)	1.30E-09	5.60E+04
		Estimate	Std. Error	Z value	Pr(>|z|)	Nagelkerke pseudo R2		
age		2.60E-03	0.01	0.47	0.64	1.11E-03		

	link	threshold	nobs	logLik	AIC	niter	max.grad	cond.H
loglog Coefficients:		flexible	213	-232.23	472.46	6(1)	1.49E-08	6.70E+04
		Estimate	Std. Error	Z value	Pr(>|z|)	Nagelkerke pseudo R2		
age		1.28E-02	0.01	2.18	0.03 *	0.02		

	link	threshold	nobs	logLik	AIC	niter	max.grad	cond.H
loglog Coefficients:		flexible	213	-226.47	460.93	6(0)	2.43E-10	8.50E+04
		Estimate	Std. Error	Z value	Pr(>|z|)	Nagelkerke pseudo R2		
age		0.03	**6.10E-03**	4.19	**2.81E-05**	0.09		

4. Discussion & Conclusions

The results indicate that entheseal changes cannot be used to predict these occupation categories, using raw data or asymmetries (side or between muscle groups): age appears to have a stronger effect.

- Part of the problem may lie in the different age structures for the occupation categories which may be reinforced by the supervised model.
- Occupation categories based on an individual's final occupation, may not be the most appropriate assessment of biomechanical loading so future research should use other measures, e.g. cross-sectional geometry.
- Further research on the aetiology of entheseal changes may lead to the exclusion of some changes for studies of activity: improving data quality.
- This sample has few individuals who undertook non-manual compared to heavy manual labour, therefore larger and more diverse skeletal collections are needed for future studies.

References

Alves Cardoso, Henderson. 2013. Int J Osteoarchaeol 23: 186–196.
Henderson, et al. 2013. Int J Osteoarchaeol 23: 152–162.
Henderson et al. 2017. BMSAP DOI: 10.1007/s13219-017-0185-x
Jurmain et al. 2012. In A Companion to Paleopathology, Grauer A (ed). Wiley/Blackwell; 531–542.
Liaw & WIener 2015. https://www.stat.berkeley.edu/~breiman/RandomForests/
Michopoulou et al. 2015. Am J Phys Anthropol 158: 557–568.
Villotte et al. 2010. Am J Phys Anthropol 142: 224–234.
Villotte et al. 2016. Int J Paleopathol 13: 49–55.

Acknowledgements. Research funded by Fundação para a Ciência e a Tecnologia SFRH/BPD/82559/2011 and support for conference attendance Pest-OE/SADG/UI0283/2013. Fundação para a Ciência e a Tecnologia is supported by PoPH and EU. A big thank you to David Navega for initial guidance on using random forests.