"UNSCRAMBLING" MULTIVARIATE DATA FROM MIXTURES:

I: FAT, WATER AND PROTEIN DETERMINATION IN MEAT BY NEAR-INFRARED REFLECTANCE SPECTROSCOPY.

II: SOY PROTEIN AND COLLAGEN DETERMINATION IN MEAT PRODUCTS FROM AMINO ACID DATA.

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INTRODUCTION T.

"You cannot unscramble an egg" it is said. But you can, if you have a computer! Two examples will illustrate the potential of multivariate statistical analysis in meat science. The first one shows how a single, rapid light-reflectance measurement may yield the fat unter and exterior and exterior and exterior shows how a single shows light-reflectance measurement may yield the fat, water and protein percentages in meat. The second one shows how various soy proteins (and other protein entry) how various soy proteins (and other protein extenders) may be quantified in meat products from amino acid ana lysis.

The rapid development of various multi-variate quantitative instruments in analytical chemistry hold a great promise for "unscrambling" mixtures is a for curtification of the second se promise for "unscrambling" mixtures, i.e. for quantitative analysis of individual components in systems such as hecome meat products. Measurements may be performed on more or less intact samples, - therefore the analyses become simple and fast, and the risk of preparation artifactor

However, many modern analytical instruments may create a vast number of data: for lack of adequate information handling methods this creates data overflow in the rind of the handling methods this creates data overflow in the mind of the many researchers! It appears that the numerical tools of many chemists today are the same as they were 20 minutes and the many researchers! tools of many chemists today are the same as they were 30 years ago: means and standard deviations. With a computer programmed for multivariate analysis colevent is for the same as they were solver the same as they were solver to be a standard deviation. puter programmed for multivariate analysis, relevant information may be compressed and displayed for optimal interpretation, while much of the noise and repetitive reduction may be compressed and displayed for optimal

Multivariate "unscrambling" allows the use of non-specific measurements for specific quantitative analyses simple bi-variate example, well known in biochemistry, is the determination of protein concentration by $\frac{1}{260}$ sorbition, where the disturbance of nucleic acids at 280 nm is climicated. sorbition, where the disturbance of nucleic acids at 280 nm is eliminated by reading the absorbance at both 10^{-2} for and 280 nm and taking a difference. In general, a mixture of N difference by reading the absorbance at both 10^{-1} for a mixture of N difference. and 280 nm and taking a difference. In general, a mixture of N different components may be "unscrambled" yield the concentrations of each of the components, from N different measurements on the same mixture s^{ample} . The N measurements may be completely non-specific, i.e. all N components for the same mixture s^{ample} . The N measurements may be completely non-specific, i.e. all N components may affect the reading for all N measurement methods, as long as the statistical requirement for all N components may affect the reading for all successful to the statistical requirement for the statistical requir surement methods, as long as the statistical requirement of linear independence is fulfilled: The N-dimensional N measurement "spectrum" corresponding to 100% purity of a component must be "unique", i.e. at the precision level of the instruments it must be sufficiently different from the "unique", i.e. at the precision of the instruments it must be sufficiently different from the "unique". level of the instruments it must be sufficiently different from the "spectra" of the other (N-1)components, also different from any linear combination of them. The greater the "uniqueness" of a component's "spectrum is, the greater will the precision of the obtained concentration

Since all measurements contain random errors, it is advantageous to have <u>more</u> measurements than unknown composition in the system, and to balance the errors is the difference of the system. nents in the system, and to balance the errors in the different measurements against each other by e.g. weighted least squares technique. This increases the precision of the obtained concentration results, provided the additional measurements yield relevant signals, and not only irrelevant site additional measurements and the second state of the se the additional measurements yield relevant signals, and not only irrelevant noise. Computations then require a computer, in contrast to the biochemists' manual "two equations - two values of the val

The "unscrambling" techniques relies on an initial "calibration" of the statistical model later to be used with unknown samples. This calibration depends on the model and new with the statistical model later to be used with the statistical model with the statis unknown samples. This calibration depends on the model and may either be based on some standard multivariate ("action of the statistical method to convert the measured "spectrum" into the concentration of some standard multivariate ("action of the statistical method to convert the measured "spectrum" into the concentration of the statistical method to convert the measured "spectrum" into the concentration of the statistical method to convert the measured "spectrum" into the concentration of the statistical method to convert the measured "spectrum" into the concentration of the statistical method to convert the measured "spectrum" into the concentration of the statistical method to convert the measured "spectrum" into the concentration of the statistical method to convert the measured "spectrum" into the concentration of the statistical method to convert the measured "spectrum" into the concentration of the statistical method to convert the measured "spectrum" into the concentration of the statistical method to convert the measured "spectrum" into the concentration of the statistical method to convert the measured "spectrum" into the concentration of the statistical method to convert the measured "spectrum" into the concentration of the statistical method to convert the measured "spectrum" into the concentration of the statistical method to convert the measured "spectrum" into the concentration of the statistical method to convert the measured "spectrum" into the concentration of the statistical method to convert the measured "spectrum" into the concentration of the statistical method to convert the measured "spectrum" into the concentration of the statistical method to convert the measured "spectrum" into the concentration of the statistical method to convert the spectrum of the statistical method to convert the statistical method to convert the statistical method statistical method to convert the measured "spectrum" into the concentration of the components of interest ("separate, empirical" calibration), or it may be based on a detailed under the detailed under the components of are gent ("separate, empirical" calibration), or it may be based on a detailed understanding of how the signals are gene rated in the samples and recorded in the instrument. ("simultaneous architic and in the signals are gene"

Both approaches are illustrated in the instrument, ("simultaneous analytical" calibration). given elsewhere^{1,2}. The first example concerns near-infrared (NUP) actions calibration techniques and the second secon given elsewhere^{1,2}. The first example concerns near-infrared (NIR) reflectance measurement of fat, water has water has and protein in raw meat. Here each component (fat, water and protein) is a supervised of the supervised of protein in raw meat. Here each component (fat, water and protein) is calibrated for separately. NIR hitherto found minimal use in meat science³, while being well accepted in cereal and dairy science. Norris recently tested the method for fat in fried meat; Technicon Corp.⁵ has tested it for cooked meat products.

The second example, determination of various protein types in a meat product from its amino acid (a.a.) comp sition, involves simultaneous quantification of all and a second sec sition, involves <u>simultaneous</u> quantification of all major protein components. Analyses of protein mixtures from a.a. data is well established^{1,6} ⁸ although not in meat science

2. EXAMPLES

Ι. Fat, water and protein determination in meat by near-infrared reflectance spectroscopy

Components such as fat, water, protein, starch etc. exhibit overlapping, but somewhat different light absolution of the source o bance spectra in the 1400-2600 nm wavelength region (Fig. 1). These Near-IR (NIR) absorbance spectra may obtained as "apparent absorbance" from log (1/reflectance) at various usual states are absorbance spectra may be measured for which the spectra may be may be measured for which the spectra may obtained as "apparent absorbance" from log (1/reflectance) at various wavelengths. The apparent absorbance spectra mail tational systems, powders, moist samples as well as liquide. Sector a computational systems and computational systems are apparent absorbance and computational systems. be measured for solid samples, powders, moist samples as well as liquids. Several different optical and comp tational systems are available. A Technicon Infralyzer 400 was used protectly and different optical and wi tational systems are available. A Technicon Infralyzer 400 was used presently. The instrument was equipped and fixed wavelength bandpass filters.

38 commercial bovine and porcine meat cuts were used³ as samples. They were homogenized, and fat, ^{water} ^{prod} protein content were determined by standardized analyses (fat by Forlet were homogenized, and fat, ^{water} ^{kjel} protein content were determined by standardized analyses (fat by Foslet, water by drying and protein by Kiel dahl). Fat varied from 1.6 to 84.5 per cent of wet weight, water percentage from 1.6 to 84.5 per cent of wet weight. dahl). Fat varied from 1.6 to 84.5 per cent of wet weight, water percentage varied from 8.2 to 75.0, and protein the samples water percentage from 2.4 to 23.4. the

The samples were frozen until NIR-measurements could be obtained. After thawing and tempering to $21\pm 1^{\circ}$ C, NIR reflectances of the samples at 19 wavelengths were read directly from the samples at 19 wavelengths were read directly from the samples at 19 wavelengths. NIR reflectances of the samples at 19 wavelengths were read directly from the samples in a standard measure of the sample of a Hewlett-Packard 98254 calculator rest. cup. The NIR spectra were recorded on a Hewlett-Packard 9825A calculator and the concentration of each composition of the samples in a standard measure recorded to the NIR spectrum in the 38 samples by unwards and the concentration of each composition of the samples are recorded to the NIR spectrum in the second standard standard standard to the NIR spectrum in the second standard standard standard to the NIR spectrum in the second standard nent was related to the NIR spectrum in the 38 samples by upwards and downwards stepwise multiple linear re

gression. Table 1 shows the regression coefficients thus obtained. Pig. 2 ... ^{ression}. Table 1 shows the regression coefficients thus obtained. ¹/₈, 2 shows the relationship between the fat content determined "conventionally" and by the NIR "unscrambling" ¹⁸ 2 shows the relationship between the fat content determined "conventionally" and by the Min difference of wet weight; the ¹⁰ convention of the 38 samples analyzed. Standard errors of the NIR estimate was 1.1 percent of wet weight; the ¹⁰ convention of the 38 samples analyzed. Standard errors of the corresponding standard errors (and correlation correlation coefficient was r=0.999. For water and protein the corresponding standard errors (and correlation Coefficient Co $c_{0efficients}^{clation}$ coefficient was r=0.999. 101 and 0.7 percent (r=0.999) and 0.7 percents.

percent (r= 0.990), respectively. computerized NIR instrument was easy to

 p_{erate} , and once calibrated it required less t_{han} , water and pro $t_{h_{an}}^{eecate}$, and once calibrated it requires to $t_{h_{an}}^{eecate}$, and protein Percentages in an unknown homogenized, Percentages in an unknown non-tion characteristic sample. The calibra-tion characteristic sample. The calibra-teristic sample. The calib obtained was tested briefly on some additional samples with known composition with some a high $v_{i_{th}}^{u_{tlional}}$ samples with known composition $v_{i_{th}}^{satisfactory}$ results. However, a high $\rho_{0_{s_{i_{tip}}}}$ (770.95) between the Positive correlation (r=0.95) between the same v_{ater} and protein percentages in the 38 samp-leg w_{ae}) because the meat les was observed, apparently because the meat cuts primarily varied in fat/muscle ratio. This implies that future meat samples with atypical water/protein ratioes would probably be less well characterized by the calibrate calibration constant values obtained here. Adding some atypical samples to the set of calibration atypical samples to the set of calibration samples should eliminate this Potential problem.



Several Problem. tequire function of the NIR-reflectance method Figure 1: (NIR absorbance) Spectra of pure fat, pure water and pure protein⁵. The vertical lines illustrate the approximate ^{veral} ^{aspects} of the NIR-reflectance method ^{figure 1}: (NIR absorbance) Spectra of pure fact, part and tempera-^{ture} further attention: pH- and tempera- pure protein⁵. The vertical lines illustrate the approximate ^{figure 1} induced "chemical shifts" in the NIR maxima of the 19 bandpass filters in the Infralyzer 400. The ^{spectra} induced "chemical shifts" in the NIR spectrum of starch is also given. The spectra are given with ture ^{he} ^c ^{ind} ⁱⁿ Approx and their physical states, determined their physical states, determined bares, determined bares

^{Vul}linearities at very high apparent absor-("mirror-")reflectance etc. These possible complications may have to be understood before a simultaneous, ana-^{Vul}linearities at the water peak maximum), the "whiteness" of samples (PSE- vs DFD-meat), the effects of specular ^{Vul}linearities at very high apparent absor-("mirror-")reflectance etc. These possible complications may have to be understood before a simultaneous, ana-^{Vul}linearities at the water peak maximum and the sample of the sample ly^{stro}r-") reflectance etc. These possible complications may have to be understood before a simultaneous, ^{complication} NIR calibration may be developed, yielding a "lack-of-fit" measure of each sample. However, once these (etcation) Will NIR calibration may be developed, yielding a "lack-of-fit" measure of each sample. Monthly in more etailed and are understood, then they may possibly open some new and exciting applications of NIR in more here and any are understood, then they may possibly open some new and exciting applications of NIR in more also d^{applications} are understood, then they may possibly open some new maples. ^{this d} analysis of the chemical composition and physical state of samples. ^{this prel:}

preliminary study indicates that the commercial NIR reflectance "unscramblers" presently available are al-y suitors and study indicates that the commercial NIR reflectance "unscramblers" presently available are already suitable for routine analysis of fat, water and protein in meat cuts.

II. Robust analysis of soy protein and collagen contents in a meat product from its amino acid composition

Present it is difficult to measure quantitatively the concentration of soy protein in meat products, especially textured s

- W.	Wavelength,	Regression coefficients					
/		Fat	Water	Protein			
	2384	593.78	-1218.99				
	2336	- 702.85	1594.04				
	2310			- 128.11			
	2270			362.55			
	2230			-1183.43			
	2208			1044.72			
	2190	1461.60					
	2180	-2170.51	666.02				
	2139		-1217.84				
	2100	928.88					
	1982			- 248.89			
	1940	- 84.52	22.53	186.79			
	1818		- 827.33				
	1/78	-1971.36	4000.29				
	1/59	3092.19	-4219.62	206.20			
	1/34	- 259.54	360.12	110.99			
	1/22	- 727.86	649.70				
_	1080			69.46			
nt	1445 ter	- 180.25	205.37				
	erm:	35 35	52.13	10.74			



Figure 2: Fat percentages in raw meat cuts, obtained by NIR, compared to those obtained in the same samples by a conventional method (Foslet). 38 samples, 11 NIR filters used (col. 1, Table 1). St.error of estimate: 1.1 percent of wet weight; correlation coefficient r=0.999.

Product feasibility study investigates whether unscrambling of the amino acid (a.a.) spectrum of a modulate the soy protein concentration to the satisfactory accuracy. The idea is that the a.a. compo-major of a modulate the soy protein concentration to the satisfactory accuracy. The idea is that the ach of the Present feasibility study investigates whether unscrambling of the amino acid (a.a.) spectrum of a meat Roduct Can Vield the soy protein concentration to the satisfactory accuracy. The idea is that the a.a. comparison of a meat product may be expressed numerically as the sum of the a.a. contributions from each of the may be protein concentration to the muscle proteins, as well as of potential added proteins as the protein concentration of the muscle proteins. Aging of a meat product may be expressed numerically as the sum of the a.a. contributions from each of a may brotein sources, because the a.a. spectra of the muscle proteins, as well as of potential added proteins and sources, because the a.a. spectra of the muscle proteins model appears feasible. In the pre-"Jor of a meat the soy protein added proteins of the sum of the set as of potential added proteins as well as of potential added proteins as the accurately described. Thus a "simultaneous, analytical" unscrambling model appears feasible. In the pre-the example the described. Thus a "simultaneous, analytical" unscrambling model appears feasible. Since the guantitation of textured soy protein and soy protein isolate. Since "Y be protein sources, because the a.a. spectra of the muscle proteins," sent example the model is tested for the quantitation of textured soy protein and soy protein isolate. Since analyze the model is tested for the quantitation of textured soy protein and "non-collagen" muscle protein are ^{cample} the model is tested for the quantitation of textured soy protein and soy protein function are value the model is tested for the quantitation of textured soy protein and soy protein function are value tissue/muscle ratio may be expected to vary, both collagen and "non-collagen" muscle protein are togethe

by weighted least squares (provided that the spectra of the pure protein sources (soy etc.) are $\operatorname{precisely}_{ana}$ known, that both the pure protein sources and the unknown meat products are analyzed by exactly the same and the unknown meat products are analyzed by exactly the same and the unknown meat products are analyzed by exactly the same and lytical procedure, and that the approximate level of random error variance in the a.a. data of the unknown meat products is known in advance.)

Amino acid spectra (in gram a.a. per 100 gram recovered a.a.) obtained for (1) collagen, (2) non-collagen muscle (bovine m.semimembranosus); (3) mass (4) textured and (5) muscle (bovine <u>m.semimembranosus</u>); (3) mean, (4) textured and (5) untextured soy protein, and (6-8) three known soy-muscle mixtures. Litterature values given for caseinate⁹ and blood serum protein¹⁰ lack proline values. "Per cent recovery per 16 gram N" represent the spectrum sum when the a.a. are given in gram a.a. per 16 g^{ram} N "n" shows the number of gram because the spectrum sum when the analysis of the spectrum sum when the s

N. "n" shows the number of spectra used for calculating the average spectra in the table.

COLUMN	1	2	3	4	5	6	7	8	9	10
		Meat	1-H-	Soya			Mixtures			Blood
SAMPLE:	Collagen	Non-collagen	Mean	Textured	Untextured	T1	T2	U	Caseinate	serum
a.a.			÷							
ASP	7.17	9.39	11.78	11.89	11.57	10.17	10.67	10.11	7.81	11.17
THR	2.39	4.27	3.33	3.38	3.23	3.88	3.90	3.93	4.47	4.79
SER	3.50	3.86	4.93	4.93	4.93	4.10	4.39	4.11	5.89	5.96
GLU	13.47	17.31	19.24	19.06	19.60	16.88	17.33	16.86	23.05	9.89
PRO	12.84	5.44	6.63	6.46	6.91	5.63	5.17	5.72	-	-
GLY	10.10	4.76	4.14	4.18	4.07	4.74	4.55	4.50	2.09	4.89
ALA	8.93	5.81	4.35	4.41	4.22	5.66	5.44	5.64	3.30	8.29
VAL	3.68	4.94	4.81	4.78	4.88	5.03	4.79	5.28	7.16	8.61
ILE	2.20	4.90	4.62	4.59	4.68	4.77	4.85	4.89	5.38	1.49
LEU	4.71	8.22	7.77	7.69	7.92	8.28	8.36	8.36	9.97	12.8/
TYR	1.64	3.79	3.64	3.55	3.82	3.57	3.47	3.62	5.78	3.40
PHE	2.85	4.24	5.22	5.19	5.28	4.46	4.47	4.45	5.35	7.13
LYS	5.05	9.39	6.39	6.44	6.27	8.56	8.42	8.75	8.65	8.51
HIS	1.57	3.92	2.65	2.70	2.56	3.65	3.57	3.66	3.25	6.00
ARG	8.18	6.15	7.72	7.77	7.63	7.01	7.16	6.62	4.08	4.41
CYS(OX)	0.43	0.93	1.44	1.57	1.20	1.26	1.31	1.18	0.60	0.85
MET (OX)	1.32	2.69	1.34	1.34	1.24	2.36	2.16	2.34	3.18	1.60
% recovery										
per 16 g N	90.55	96.50	100.94	100.45	102.02	98.37	97.51	97.86	97.25	94.00
n	4	2	3	2	1	1	1	1		mato

graphy from collagen (porcine skin, 2 parallels; porcine tendon, 2 par.), muscle (bovine <u>m.semimembranosus</u>, so collagen, 2 par.), a textured soy protein (P.P.50, containing 57% crude protein, 2 par.) and a soy protein is late powder (Supro 500, 93% crude protein). Compared to collagen and protein the term of the protein protein protein protein (P.P.50) and a soy protein (P.P.50). late powder (Supro 500, 93% crude protein (P.P.50, containing 57% crude protein, 2 par.) and a soy protein rein were very similar (col.4-5). In order to increase the precision of the matching the two types of pure soy protein collar were very similar (col.4-5). In order to increase the precision of the modelling spectra, means of the 4 collar gen spectra, of the 2 muscle spectra. gen spectra, of the 2 muscle spectra,

and of all 3 soy protein spectra were used in the calculations, (col. 1-3). In addition three known "meat products" (raw mixtures of soy protein and bovine m.semimembranosus), were analyzed (col. 6-8). Four pairs of parallel a.a. spectra were available to estimate the standard deviation of random analytical errors in the present analytical procedure: The obtained regression equation was: (st. dev. =0.06+0.02x signal). Zero covariance was assumed for simplicity. Table 3 compares the obtained soy protein concentrations to the correct ones, in samples ranging from 100% to. 0% soy protein. The concentration was calculated in two units: Normalizing every a.a. spectrum to a sum of 100% (i.e. "g a.a. per 100 g recovered a.a") prior to the calculations yielTable 3: Soy protein concentrations: Comparison between the star tistically calculated and the correct percentages.

Col.	l Calculat % real protein	ed ^{a) 2} % crude protein	3 Correct % crude protein	4 Difference % crude protein
Soy protein	99.9±3.4(n=3)	99.8±3.3	100.0	0.2±3.3
T1= Textured Soy	35.7	34.8	37.6	2.8
T2= Textured Soy	26.5	25.8	23.2	-2.6
U = Untextured Soy	24.1	23.4	21.3	-2.1
Muscle	-0.1±2.6 (n=2)	-0.1±2.6	0	-0.1±2.6
Collagen	-0.1±1.4 (n=4)	-0.1±1.4	0	-0.1±1.4

a) A model containing collagen, muscle and soy protein (Cols 1,2 and 3, Table 3) was used, with muscle protein=100% - collagen soy protein. Error std.dev.=0.06+0.02xsignal was used for weighting. ting.

butions from the missing a.a. (tryptophane and hydroxy-proline), col. 1 gives soy concentrations in "g true" protein per 100 g total true protein", a unit which would be inconstitute from solutions in "g true" protein per 100 g total true protein", a unit which would be insensitive to possible frauds by added non protein tein nitrogen. Col. 2 shows the corresponding results after conversion to the conventional "g crude soy protein per 100 g total crude protein". The correct soy protein percentages (col. 2) are visional "g crude soy protein Crude protein is taken and the correct soy protein percentages (col. 2) are visional "g crude soy protein". Crude protein is taken as Kjeldahl-Nx6.25. Inspecting the lack-of-fit between the measured and the reconstructed a.a. spectra showed systematically higher residuals than expected for the measured and the reconstruction of the residuals than expected for the measured and the reconstruction of the reconstruct ted a.a. spectra showed systematically higher residuals than expected for cystein, indicating an abnormalic high analytical variance. However, in the present preliminary study no offers of cystein, indicating an abnormalic for this high analytical variance. However, in the present preliminary study no effort was made to correct for 0.3% and the the total crude protein was thus obtained in the total crude protein to An average error of less than 3% of total crude protein was thus obtained, implying an error of less that 0.3% of product wet weight, for meat products containing about 10% protein. Thus of product wet weight, for meat products containing about 10% protein. Thus, a.a. unscrambling gave quite accur rate soy protein concentrations in raw "meat products", as well as in product, a.a. unscrambling gave quite and pure rate soy protein concentrations in raw "meat products", as well as in pure soy, pure connective tissue and pure muscle .

However, submitting the spectra of two autoclaved, soy-free meat products (not shown here) to the same a, a model yielded rather high residuals and appreciable calculated "amounts of the same a, b the same a, b the same between the same and appreciable calculated "amounts of the same between th model yielded rather high residuals and appreciable calculated "amounts of soy". This indicates that the ^{spectrum} is modified significantly during strong heat treatment. Work is therefore in progress to modify the ^{table} by "regression on disjoint factor analysis models"², to allow for this heating effect (and other predictable types of variabilities).

At present the unscrambling method was only tested on a few physical meat samples. However, the conclusions so far were Were supported by purely statistical considerations: Since the basic mixtures model used here is a linear tegression model, the expected error standard deviation of an obtained soy protein concentration may be calcu-lated to the present data, the model involving lated theoretically². At the error level found between replicates in the present data, the model involving Collagen theoretically². At the error level found between replicates in the present data, the model of the protein. This correspondences and soya yielded a soy protein standard deviation of 3.0 percent of total crude protein. This for the protein standard deviation of a separate calculations on a.a. spectra from Corresponds well to the error level found above and was confirmed in separate calculations on a.a. spectra from the life the literature.

Assuming 10 per cent protein in a meat product and using two standard deviations in order to ensure about 90% Probability per cent protein in a meat product to a sov protein error limit of ± 0.6% of product wet weight. $p_{robability}$ of fraud detection, this corresponds to a soy protein error limit of ± 0.6% of product wet weight. th other words, if the legal limit of soy protein addition in a meat product is e.g. 3% of product wet weight, then it there words, if the legal limit of soy protein addition in a meat product is e.g. 3% soy protein. then it should theoretically be possible to "arrest" products that contain more than 3.6% soy protein.

Increasing the analytical accuracy, e.g. by taking parallel analyses, would narrow the error limits correspond-

The error limits of collagen and non-collagen muscle protein were calculated to be about \pm 0.4 and \pm 0.5% of moduct we Product wet weight.

The unscrambling method was likewise tested theoretically for simultaneous analysis of both soy protein, case inate and the data for the caseinate⁹ and serum protein¹ inate and blood serum protein in meat products, using litterature values for the caseinate⁹ and serum protein¹⁰ (Table 3, col.9-10).

The 3, col.9-10). The results were quite promising. Again assuming a level of random errors equal to that found in the present data, the data results were quite promising. Again assuming a level of random errors equal to that found in the error standard deviations of obtained crude protein concentrations (in percent of total crude protein) were error standard deviations of obtained crude protein 2.5 for caseinate. 2.0 for blood plasma protein, 1.5 for collain) the error standard deviations of obtained crude protein concentrations (in percent of total concentrations) were calculated to be 3.5 for soy protein, 3.5 for caseinate, 2.0 for blood plasma protein, 1.5 for colla-Ren and 3.5 for muscle protein. Work is in progress to examine this in more detail, as well as to test alterna-tive states for muscle protein. Work is in progress to examine the states of the state t_{ive}^{and} 3.5 for muscle protein. Work is in progress to examine the A_{a} , A_{a} , analytical methods (e.g. incorporating non-negativity requirements).

analysis is today an expensive, but with alternative analytical techniques (fully automated instruments, hplc etc.) complete or partial a.a. analysis may become cheaper.

CONCLUSION

The reflected NIR light spectra of meat could be unscrambled to yield fat, water and protein contents. Thus NIR reflectance NIR light spectra of meat could be unscrambled to yield fat, water and protein contents. Thus NIR reflected NIR light spectra of meat could be unscrambled to yield ter, lequectance appears to be feasible for fast and simple meat characterization. the suring the second and untextured soy protein, as well as ot

Westance appears to be feasible for fast and simple meat characterization. Westance appears to be feasible for fast and simple meat characterization. Westance appears to be feasible for fast and simple meat characterization. aucts seems feasible by multivariate "unscrambling" of amino acid data.

In seems feasible by multivariate "unscrambling" of amino acid data. Centration a non-specific multivariate measurement from an unknown meat sample was used to yield the concentrations of the individual constituents.

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