

1 **Interpretative summary: Visible and near-infrared bulk optical properties of raw milk.**

2 **Aernouts.**

3 The quality of milk is important for the dairy farmer, milk processing plants, retail and
4 the consumer. Optical techniques based on Vis/NIR spectroscopy have already proven their
5 potential for automated monitoring of the milk composition and microstructure as these
6 properties are related to respectively the absorption and scattering of light. Nevertheless, the
7 interaction between absorption and scattering of the light travelling through the sample
8 complicates the interpretation of the measured signals. Therefore, the sensor should be well
9 designed and combined with a robust light propagation model to obtain accurate predictions of
10 the milk properties. In this paper, the Vis/NIR bulk optical properties of raw milk are studied
11 and reported. This information is essential for the optimization of a Vis/NIR optical milk quality
12 sensor.

13

14 **VISIBLE AND NEAR-INFRARED BULK OPTICAL PROPERTIES OF RAW MILK**

15

16 **Visible and near-infrared bulk optical properties of raw milk**

17

18 **B. Aernouts, R. Van Beers, R. Watté, T. Huybrechts, J. Lammertyn, and W. Saeys**

19 KU Leuven, Department of Biosystems, MeBioS, Kasteelpark Arenberg 30, 3001 Leuven,
20 Belgium.

21

22 Corresponding author: Ben Aernouts, KU Leuven, Department of Biosystems, MeBioS,
23 Kasteelpark Arenberg 30, 3001 Leuven, Belgium. Phone: +32 16 321470, Fax: +32 16
24 321994, E-mail: Ben.Aernouts@kuleuven.be

25 **ABSTRACT**

26 The implementation of optical sensor technology to monitor the milk quality on dairy
27 farms and milk processing plants would support the early detection of altering production
28 processes. Basic visible and near-infrared (Vis/NIR) spectroscopy is already widely used to
29 measure the composition of agricultural and food products. However, to obtain maximal
30 performance, the design of such optical sensors should be optimized with regards to the optical
31 properties of the samples to be measured. Therefore, the aim of this study was to determine the
32 Vis/NIR bulk absorption coefficient, bulk scattering coefficient and scattering anisotropy
33 spectra for a diverse set of raw milk samples originating from individual cow milkings,
34 representing the milk variability present on dairy farms. Accordingly, this database of bulk
35 optical properties can be used in future simulation studies to efficiently optimize and validate
36 the design of an optical milk quality sensor. In a next step of the current study, the relation
37 between the obtained bulk optical properties and milk quality properties was analyzed in detail.
38 The bulk absorption coefficient spectra were found to mainly contain information on the water,
39 fat and casein content, while the bulk scattering coefficient spectra were found to be primarily
40 influenced by the quantity and the size of the fat globules. Moreover, a strong positive
41 correlation ($R \geq 0.975$) was found between the fat content in raw milk and the measured bulk
42 scattering coefficients in the 1300 – 1400 nm wavelength range. Relative to the bulk scattering
43 coefficient, the variability on the scattering anisotropy factor was found to be limited. This is
44 because the milk scattering anisotropy is nearly independent of the fat globule and casein
45 micelle quantity, while it is mainly determined by the size of the fat globules. As this study
46 shows high correlations between the sample's bulk optical properties and the milk composition
47 and fat globule size, a sensor which allows for robust separation between the absorption and
48 scattering properties would enable accurate prediction of the raw milk quality parameters.

49

50 **Keywords:** Milk, fat globule, casein micelle, Visible and near-infrared spectroscopy,
51 scattering, absorption, optical sensor design

52 INTRODUCTION

53 A precondition for increased profitability in dairy farming is an increase in both the
54 lactation and lifetime production per cow. Therefore, more effective prevention and early
55 treatment of all diseases, especially the so-called 'production diseases', is needed (Hamann and
56 Krömker, 1997). To meet these demands, individual cow and udder health should be carefully
57 monitored. Since the milk production is a dominant factor in the metabolism of dairy cows,
58 involving a very intensive interaction with the blood circulation, the extracted milk contains
59 valuable information on the nutritional, metabolic and infectious status of the cow (Aernouts et
60 al., 2011; Løvendahl et al., 2010; Forsbäck et al., 2010, 2009; Friggens et al., 2007; Mulligan
61 et al., 2006; Hamann and Krömker, 1997). Therefore, regular analysis of the produced milk is
62 considered to be the most efficient way to monitor cow and udder health. Online measurement
63 of the milk components (fat, protein, lactose, etc.) during milking twice a day would offer the
64 potential for early detection of systemic and local alteration, thus providing a valuable input for
65 strategic and operational management decisions (Friggens et al., 2007).

66 Visible (Vis) and near-infrared (NIR) spectroscopic analysis of raw milk allows for a
67 reliable detection of the fat, protein and lactose concentration in the lab (Aernouts et al., 2011).
68 The prediction of this milk composition is mainly based on the wavelength-dependent
69 absorption of Vis/NIR radiation by the milk constituents. The industry has recently adopted this
70 technology, and implemented it into milking systems to measure the major milk components
71 on-line (Pinsky et al., 2013; Katz et al., 2011, 2003). However, despite of the continuous
72 recalibration, their accuracy and robustness is still not sufficient to support cow health
73 management (Kaniyamattam and De Vries, 2014). This is mainly because the measured spectral
74 signals are, next to absorption, considerably influenced by the physical properties of the milk

75 in terms of the quantity and size of the fat globules and casein micelles. Since the refractive
76 indices of milk fat and casein differ from that of the milk serum, the Vis/NIR radiation is forced
77 to deviate from its straight trajectory (Tuchin, 2007). Because of these scattering processes, the
78 travelling path of the radiation increases to an unknown extent. This complicates the prediction
79 of the composition from measured spectra. Homogenization of the milk fat globules could
80 reduce and standardize the Vis/NIR scattering to improve the prediction results. For example,
81 in the early days of milk analysis, the Milko-tester (Foss Electric, Hillerød, Denmark) measured
82 the Vis scattering after dispersion of the casein micelles and homogenization to produce a more
83 uniform fat globule size distribution. Accordingly, the light attenuation depends mainly on the
84 amount of fat globules and can, therefore, be used to obtain a rough estimate for the fat content
85 (McDowell, 1968). However, because of its destructive character, high energy consumption
86 and significant wear and tear, the proceeding homogenization step is not desired in online
87 analyses on-farm. Alternatively, the non-linear interference due to light scattering can be
88 reduced with empirical methods (e.g. baseline correction, derivatives, ...) or over-simplistic
89 scattering models (e.g. normal, piecewise and extended multiplicative scatter correction, path
90 length correction method, ...) and/or can be partially accounted for by the prediction models
91 (e.g. partial least squares, support vector machines, ...) (Aernouts et al., 2011). However, these
92 techniques only provide acceptable results for samples with absorption and scattering properties
93 similar to those consulted in the calibration procedure (Melfsen et al., 2013). As the quantity
94 and size of the fat globules and casein micelles for different fresh raw milk samples experiences
95 large variations, the scattering properties too vary a lot (Logan et al., 2014; Cabassi et al., 2013;
96 Nielsen et al., 2005; Vangroenweghe et al., 2002). Consequently, it is very challenging to fully
97 compensate for all this scattering variability with a single empirical calibration model.
98 Therefore, more powerful and advanced techniques are needed to remove the scattering
99 interference from the measured Vis/NIR spectra (Melfsen et al., 2012).

100 In Vis/NIR spectroscopy, accurate separation of the absorption and scattering properties
101 would reduce the need for empirical scatter corrections and promote robust prediction of the
102 sample composition (Steponavičius and Thennadil, 2013, 2011; Steponavicius and Thennadil,
103 2009). Moreover, the pure absorption, defined as the bulk absorption coefficient μ_a (cm^{-1}), is
104 the probability of absorption per unit infinitesimal path length at a specific radiation wavelength
105 and relates directly to the sample composition according to the Beer-Lambert law. The
106 scattering, on the other hand, can be described with the bulk scattering coefficient μ_s (cm^{-1}) and
107 the angular scattering pattern or scattering phase function. The bulk scattering coefficient
108 defines the probability of scattering per unit infinitesimal path length in a similar way as μ_a
109 represents the absorption. The scattering phase function is generally too complex to reproduce
110 and interpret and is, therefore, often represented by its mean cosine: the scattering anisotropy
111 factor g . The scattering anisotropy for biological tissues and fluids in the Vis/NIR range varies
112 between 0 (isotropic scattering) and 1 (complete forward scattering) (Tuchin, 2007). These
113 scattering properties are determined by the physical microstructure properties of the sample
114 (e.g. particle size distribution, particle volume concentration, material properties, ...). For milk,
115 this primarily relates to the quantity and size of the suspended fat globules and, to a smaller
116 extend, the casein micelles (Aernouts et al., 2015; Bogomolov et al., 2013; Bogomolov and
117 Melenteva, 2013; Dahm, 2013; Kucheryavskiy et al., 2014; Bogomolov et al., 2012). As these
118 properties affect the physicochemical, functional and sensory characteristics of the raw milk
119 and derived dairy products, they are important quality parameters (Cabassi et al., 2013;
120 Schenkel et al., 2013; Walstra et al., 2006; Michalski et al., 2004, 2003). Moreover, the size of
121 fat globules in milk from infected udder quarters (mastitis) is increased significantly and could,
122 therefore, give insight into the udder health status of each individual cow and udder quarter
123 (Mizuno et al., 2012; Erwin and Randolph, 1975). Accordingly, extraction of physical
124 microstructure information, such as the fat globule size distribution, from isolated scattering

125 properties would create an added value for Vis/NIR spectroscopy on raw milk (Aernouts et al.,
126 2015; Cabassi et al., 2013).

127 In a single Vis/NIR spectroscopic measurement, usually reflectance or transmittance,
128 both the effect of absorption by the chemical molecules and scattering by the physical particles
129 are inter-connected and cannot be accurately separated. Consequently, a change in the scattering
130 properties of a measured milk sample might be misinterpreted as a change in the milk
131 composition (Melfsen et al., 2012). On the other hand, multiple spectroscopic measurements in
132 a slightly different configuration are not perfectly correlated and will, therefore, be influenced
133 by absorption and scattering in a different way. The combination of such multiple measurement
134 series with an accurate model, which mathematically describes light propagation as a function
135 of the sample's bulk optical properties (μ_a , μ_s and g), could provide a successful separation of
136 the sample's absorption and scattering properties (Steponavičius and Thennadil, 2013).
137 However, superior separation between these absorption and scattering properties is only
138 feasible if the optical sensor is designed to obtain a series of multiple measurements with least
139 inter-correlation and maximum signal-to-noise levels. As the measured signals are, next to the
140 sensor architecture, determined by the sample's bulk optical properties (BOP), the optimal
141 design of such a practical sensor configuration depends on the absorption and scattering
142 properties of the samples to be measured. The effect of the BOP on the light propagation, and
143 consequently the collected spectral signals, is very complex. Therefore, the optimal design
144 cannot be calculated directly from a supplied range of BOP, though it can be determined
145 through an iterative optimization procedure. In practice, a wide range of sensor configurations
146 is physically possible. So, it is preferred to test the potential of each sensor configuration
147 through these simulations, rather than building each of them and evaluating their performance
148 from measurements on an extensive set of raw milk samples (Zamora-Rojas et al., 2014;
149 Khankin et al., 2012; Gamm et al., 2011; Cen et al., 2010; Palmer and Ramanujam, 2007;

150 Sharma et al., 2006; Liu and Ramanujam, 2006; Luo et al., 2005). The sensor configuration
151 which allows for the most robust separation between the absorption and scattering properties
152 would obviously have the highest potential to retrieve accurate predictions for the milk
153 composition (fat, protein, lactose, urea, etc.) and physical properties (fat globule and casein
154 micelle size distribution) from respectively the obtained absorption and scattering properties.
155 As these milk quality properties are highly correlated to cow health, such sensor would support
156 on-farm dairy management.

157 The Monte Carlo (MC) method for simulation of light propagation is a very accurate,
158 flexible and is widely used in tissue optics (Tuchin, 2007). Therefore, it is particularly suitable
159 to simulate the collected spectra series for each sensor configuration and for the range of BOP
160 found in raw milk samples. Accordingly, the potential of each sensor configuration can be
161 defined as the ability to extract the BOP from the collected signals, after adding noise typical
162 for a Vis/NIR spectrometer. Such procedures of sensor design optimization have been widely
163 studied and improved in the last decade and are still an important topic of research (Zamora-
164 Rojas et al., 2014; Khankin et al., 2012; Gamm et al., 2011; Cen et al., 2010; Palmer and
165 Ramanujam, 2007; Sharma et al., 2006; Liu and Ramanujam, 2006; Luo et al., 2005). However,
166 in order to consult these algorithms to obtain an optimal sensor design for quality control of
167 raw milk, knowledge on the Vis/NIR BOP of raw milk is crucial.

168 Recently, the influence of a varying fat globules size on the Vis/NIR scattering
169 properties of milk was studied in detail (Aernouts et al., 2015). Moreover, reduction of the fat
170 globule size resulted in a higher wavelength-dependency of both the bulk scattering coefficient
171 and the scattering anisotropy factor, reducing their values for wavelengths above 600 nm and
172 approaching the Rayleigh scattering phenomenon. Nevertheless, to our knowledge, no accurate
173 information is available in literature on the mean, the variability and the range of the Vis/NIR
174 bulk optical properties of raw milk from dairy cows, therefore defined as the main objective of

175 this study. The measurements focus on the 550 – 1900 nm wavelength range as, below 550 nm,
176 the main milk components have no relevant absorption peaks, while above 1900 nm, water is a
177 very strong absorber resulting in very low signal-to-noise levels for any type of optical
178 measurement. Next, the obtained data was used to closely study the relation between the
179 Vis/NIR bulk optical properties and the milk's chemical and physical quality properties.

180 **MATERIALS AND METHODS**

181 *Milk samples*

182 The milk samples considered in this research were collected in the context of the milk
183 production registration system within Flanders (Belgium). Dairy farmers from all over Flanders
184 can participate in this system to monitor the milk composition and production of their individual
185 cows ones every 4 – 6 weeks. These data are used to improve breeding and genetic selection
186 and to some extent for the evaluation and basic adjustment of feeding. For each cow, a
187 representative milk sample (27 ml) is collected, preserved (4°C and $\pm 0.11\%$ v/v preservative;
188 Qlip N.V., Leusden, the Netherlands) and analyzed with the Milkoscan FT+ (Foss A/S,
189 Hillerod, Denmark) to determine the milk fat and crude protein content (ISO 9622:2000).
190 According to the fabricant, the preservative contained Patent Blue V calcium salt (CAS: 3536-
191 49-0, Sigma-Aldrich, St. Louis, MO) as a visible colorant marker. For this study, 60 raw milk
192 samples, originating from 60 different cows and 17 different dairy farms were selected from a
193 large collection of 1200 samples (20 dairy farms) to cover the maximum range of the
194 compositional variance. Moreover, the 1200 samples were ordered on fat content and the first
195 and every 40th sample was selected (total 31 samples). The same procedure was repeated for
196 the protein content on the remaining samples.

197 Table 1 gives an overview of the most important statistical parameters describing the fat
198 and crude protein content of the selected sample set. The casein content was calculated as 75.5%
199 of the crude protein content (Aernouts et al., 2015; Walstra et al., 2006). Comparison of the

200 mean, standard deviation (SD) and the range (Max – Min) of this sample set [Table 1] with the
201 same statistical parameters of a much larger dataset (Milk Control Center-Flanders) indicates
202 that the 60 samples are representative for the large population of milk produced by individual
203 cows in Flanders (Aernouts et al., 2011). The correlation between both components was found
204 to be in the normal range ($R = 0.34$) (Aernouts et al., 2011).

205

206 *Measurement of bulk optical properties for raw milk samples*

207 Double integrating sphere (DIS) and unscattered transmittance measurements were used
208 to determine the BOP of the milk samples, as this is considered to be the ‘golden standard’
209 method for BOP measurement of thin samples of turbid media. The sample illumination in this
210 setup was especially designed to obtain high signal-to-noise spectra in the 500 – 2250 nm
211 wavelength range for very turbid media like raw milk. It consists of a supercontinuum laser
212 light source (500 – 2250 nm, 4 Watt optical power) in combination with a high-precision
213 monochromator. The total reflectance (M_R) and total transmittance (M_T) were measured
214 simultaneously on each milk sample loaded in a cuvette (Schott, Germany) with a path length
215 of 600 μm and positioned between the two integrating spheres. Both spheres were equipped
216 with a Vis (400 – 1100 nm) and NIR (1100 – 2400 nm) detector. Unscattered transmittance
217 (M_U) was measured in a separate path with the Vis and NIR detectors positioned 1.5 m behind
218 the sample to limit the fraction of scattered photons collected by the detectors (Aernouts et al.,
219 2014, 2013). To obtain sufficient unscattered transmittance signal, the sample was loaded in a
220 thinner cuvette with a path length of 170 μm (Schott, Germany). A series of slits between
221 sample and detector further reduced the number of scattered photons captured in the unscattered
222 transmittance signal. For a more extensive description of the measurement setup, the calibration
223 and measurement procedure and a thorough validation, the reader is referred to (Aernouts et al.,
224 2013). Moreover, this validation study showed the high repeatability and signal-noise ratio of

225 the system to obtain the BOP of very turbid samples in the Vis/NIR (Aernouts et al., 2013). The
226 samples were thoroughly stirred before they were measured at $22\pm 1^\circ\text{C}$ (room temperature) to
227 ensure the homogeneity and temperature stability of the sample during the measurement. All
228 sample spectra were measured from 550 until 1900 nm in steps of 10 nm by automated scanning
229 of the pre-dispersive monochromator. The measurement takes 110 seconds, which was well
230 below the time span (10 minutes) after which creaming was starting to have a measurable effect
231 on the collected signals.

232 The diffuse reflectance (M_R) of the samples was derived from the total reflectance after
233 subtraction of the specular reflectance. The latter was calculated at the air-cuvette and cuvette-
234 sample interfaces through the Fresnel equations which use the real refractive indices of air (1),
235 the cuvette windows (provided by the manufacturer, Schott, Germany), and the milk sample.
236 The refractive index was calculated for each sample individually from the available milk
237 composition data, with the equation proposed by Walstra and Jenness (1984), taking into
238 account the sample temperature (22°C).

239 The inverse adding doubling (IAD) routine developed and optimized by Prahl (Prahl,
240 2010) was consulted to obtain the Vis/NIR BOP spectra from the obtained diffuse reflectance
241 and total and unscattered transmittance spectra. Because of significant contribution of scattered
242 photons, no BOP estimation could be established if the unscattered transmittance was below
243 0.01%. This was the case for approximately one third of the samples, mainly for radiation
244 wavelengths shorter than 1200 nm. If M_U was below 0.01%, this measurement was neglected
245 and an estimate for the anisotropy factor g was provided to the IAD algorithm to allow for the
246 separation of μ_a and μ_s (Prahl, 2010). For these samples, the average g spectrum was used as
247 estimate. Moreover, as the variability between the obtained g spectra was very small [Figure
248 1(c)], the average g spectrum is expected to be close to the actual g spectrum and the separation
249 between scattering and absorption should be sufficiently accurate (Prahl, 2010). Additionally,

250 also the reduced scattering coefficient μ_s' is reported. μ_s' combines μ_s and g according to the
251 similarity relation $\mu_s' = \mu_s(1 - g)$ and can be used to accurately describe scattering after
252 sufficient scattering events. In other words, after diffusion of the light, scattering can be
253 accurately described with μ_s' alone, without the need for separation between μ_s and g (Tuchin,
254 2007).

255 **RESULTS AND DISCUSSION**

256 *Variability in the bulk optical properties of raw milk*

257 The BOP spectra for all 60 raw milk samples were extracted from the measured M_R , M_T
258 and M_U spectra with the IAD algorithm. In Figure 1, the mean, mean \pm standard deviation (SD),
259 minimum (Min) and maximum (Max) values are shown for the derived BOP. The μ_a spectra
260 [Figure 1(a)] indicate a very clear signature of water, with absorption peaks around 970, 1200,
261 1450 and 1940 nm. It should be noted that the peak in μ_a around 650 nm is caused by the
262 colorant (Patent Blue V), present in the added preservative. Most of the variation in the μ_a
263 spectra can be noticed at the absorption peaks of the colorant, water and around 1220 and 1740
264 – 1770 nm. The latter wavelengths are typical absorption peaks for milk fat as they correspond
265 to respectively the second and first overtone stretch-vibrations of the CH₂-bonds (Šašić and
266 Ozaki, 2000). As the milk fat content varies between 1.52 and 12.0% (v/v) [Table 1], noticeable
267 variation can be expected at those absorption bands. Moreover, because of the water
268 displacement effect, a higher dry matter content, related to a higher fat and/or crude protein
269 content, would result in a lower absorption at the water peaks, explaining the considerable
270 variation at the water absorption peaks. Additionally, the high variability around 650 nm
271 indicates that the preservative concentration clearly varies between samples. At wavelengths
272 where nearly no absorption is expected (720 – 820 nm), still a small baseline of maximum 0.116
273 cm⁻¹ can be noticed. This is probably the result of very little cross-talk between μ_a and μ_s in the
274 BOP estimation procedure. As μ_s is relatively high (100 – 1000 cm⁻¹) compared to μ_a (0 – 35

275 cm^{-1}), little cross-talk of μ_s to μ_a is already noticeable as a small baseline, especially at
276 wavelengths where μ_a is close to zero.

277 The variation in the scattering coefficient spectra of raw milk in the 550 – 1900 nm
278 wavelength range is large, ranging from 100 until nearly 1000 cm^{-1} [Figure 1(b)]. Fat globules,
279 and to a smaller extend also casein micelles, are the main cause of scattering in milk (Aernouts
280 et al., 2015). As a result, a higher fat and casein (~protein) content, which is associated with a
281 higher quantity of respectively fat globules and casein micelles, results in an increase of the
282 bulk scattering coefficient spectra (Aernouts et al., 2014). Moreover, if scattering events are
283 uncorrelated and the size of fat globules and casein micelles is stable, there is a linear positive
284 (independent scattering) relation between μ_s and particle quantity (Aernouts et al., 2014;
285 Gaygadzhiev et al., 2008; Alexander et al., 2002). As the variation in fat and protein content in
286 the set of 60 samples is large, it is expected to be the main source of variation in the μ_s spectra.
287 Additionally, as was found in an earlier study, also the variability in the fat globule size
288 distribution between milk samples will have an important share in the μ_s variability, especially
289 for wavelengths from 550 until 1100 nm (Aernouts et al., 2015). Moreover, smaller fat globules
290 were found to result in a more steep Vis/NIR μ_s spectrum, with the maximum shifted towards
291 smaller radiation wavelengths and vice versa (Aernouts et al., 2015). The μ_s variation in the set
292 of 60 samples was found to be maximal in the 550 – 1100 nm wavelength range, with values
293 ranging from 120 until 950 cm^{-1} . This is probably because the effect of the fat globule size on
294 μ_s is maximal in this wavelength range, additional to the effect of the fat and protein content.

295 If the independent scattering condition is valid, the anisotropy spectrum should be
296 mainly influenced by the size of the fat globules, while being independent of the fat content
297 itself (Aernouts et al., 2014, 2015). As a result, the variability in the g spectra is relatively small
298 [Figure 1(c)]. In the 550 – 1900 nm wavelength range, the anisotropy factor for raw milk
299 increases steadily with increasing radiation wavelength until it reaches a maximum around 1000

300 nm (Aernouts et al., 2015). Around these wavelengths, the scattering anisotropy is maximal and
301 the fat globules in raw milk scatter most of the light in the forward direction. For longer
302 radiation wavelengths, the anisotropy factor decreases with increasing wavelength, indicating
303 more isotropic scattering. In a previous study, it was found that a higher g spectrum, mainly for
304 radiation wavelengths above 1100 nm, indicates larger milk fat globules (Aernouts et al., 2015).

305 As the reduced scattering coefficient spectrum is the result of both the μ_s and g spectrum,
306 it contains information from both the milk fat globules size and quantity. However, as all the
307 μ_s ' spectra are nearly parallel [Figure 1(d)], it seems that the effects of the fat globule size on
308 μ_s and g neutralize each other if they are combined. In the Vis/NIR, μ_s ' follows a steady
309 decrease with increasing radiation wavelength until it reaches a nearly stable level for
310 wavelengths above 1500 nm.

311

312 ***Effect of the fat globules on the bulk scattering properties of raw milk***

313 In earlier studies (Aernouts et al., 2015; Frisvad et al., 2007), it was shown that the fat
314 globules are, next to the casein micelles, the main source of Vis/NIR scattering in unskimmed
315 milk. This is because the volume fraction of the fat globules is usually larger, while the Vis/NIR
316 scattering intensities for a normalized volume fraction are also higher (Aernouts et al., 2015).
317 Additionally, relative to the fat content, the crude protein, which consists of $\pm 75.5\%$ w/w casein,
318 experiences only small variations in individual raw milk samples [Table 1] (Aernouts et al.,
319 2015; Walstra et al., 2006). As a result, the variability in the bulk scattering properties of raw
320 unskimmed milk is mainly determined by the variability in the size and quantity of the fat
321 globules. Because of this, the relation between the fat globule size and quantity, and the bulk
322 scattering properties of raw milk is discussed more in detail. In Figure 2 the bulk scattering
323 properties are shown for 6 raw milk samples with a varying fat content and a practically constant
324 crude protein content (2.36 – 2.49 % v/v). The crude protein content was kept constant to further

325 reduce the effect of casein micelles on the interpreted results. In this plot, 3 groups of each 2
326 samples can be distinguished based on the fat content, with a large variability between groups
327 and practically no variability within a group. This allows to study the effect of the fat content
328 and fat globule size separately. The μ_s spectra [Figure 2(a)] indicate that a higher fat content
329 generally results in higher Vis/NIR bulk scattering coefficients. However, within a group of
330 similar fat content, large variability can still be noticed in the μ_s spectra, especially for
331 wavelengths below 1100 nm. This is probably caused by a difference in size of the fat globules
332 between the two samples in the same group. Within the low-fat group ($3.45 \pm 0.065\%$ v/v),
333 small differences between the μ_s spectra can only be noticed for the wavelengths below 1000
334 nm. The sample with 3.51% (v/v) fat probably contains slightly smaller fat globules, as an
335 earlier study showed that smaller milk fat globules are related to a steeper μ_s spectrum in the
336 550 – 1900 nm range (Aernouts et al., 2015). The same phenomenon is even more clear for the
337 other two groups. Additionally, in these groups, a steeper μ_s spectrum in the Vis/NIR range is
338 also related to a maximum μ_s at smaller wavelengths, typical for smaller scattering particles
339 (Aernouts et al., 2015; Cabassi et al., 2013; Cattaneo et al., 2009). Within each group of raw
340 milk samples with a similar fat content, the μ_s spectra seem to cross each other in the 1200 –
341 1400 nm wavelength range. Accordingly, the μ_s in this wavelength region might be less
342 dependent on the fat globule size and have a higher correlation with the fat content itself.

343 As the anisotropy factor should be independent of the fat content if scattering processes
344 are independent, g mainly contains information on the size of the fat globules (Aernouts et al.,
345 2015, 2014). Moreover, an earlier study indicated that larger milk fat globules resulted in a
346 higher anisotropy factor in the 1100 – 1900 nm wavelength range (Aernouts et al., 2015).
347 Within each group, the sample with the smallest fat globules, according to the μ_s spectra
348 (steeper and maximum shifted towards smaller wavelengths), was also characterized by a lower
349 g spectrum for wavelengths above 1100 nm. Moreover, even between groups, a lower g

350 spectrum in the 1100 – 1900 nm wavelength range strongly correlates with a steeper μ_s
351 spectrum and a maximum μ_s at shorter wavelengths. This strengthens the hypotheses that were
352 generated in the previous paragraph.

353 The effect of the fat globule size, which is unambiguously present in the μ_s and g spectra,
354 is not clearly noticeable in the μ_s ' spectra. Moreover, while the 3 fat-content groups could
355 clearly be separated based on their μ_s spectra, only 2 distinct groups appear in the μ_s ' spectra
356 for wavelengths below 1200 nm. Furthermore, no grouping of the μ_s ' spectra can be noticed for
357 wavelengths above 1200 nm. So, it seems that the fat globule size information present in μ_s and
358 g , and the fat content information in μ_s partially neutralize each other if μ_s and g are combined.
359 This implies that μ_s ' spectra alone might be insufficient to estimate the fat globule size and/or
360 fat content and that accurate separation of μ_s and g would be required. This is, however, only
361 feasible if the unscattered transmittance can be accurately measured, or if accurate diffuse
362 reflectance and/or diffuse transmittance signals can be collected at very short source-detector
363 distances (Watté et al., 2012; Kanick et al., 2012; Prahl, 2010; Sharma and Banerjee, 2003;
364 Kienle et al., 2001).

365 As the milk fat globule quantity and size mainly determine the bulk scattering properties,
366 they also have their impact on the measured signals. The diffuse reflectance, total transmittance
367 and unscattered transmittance spectra for the 6 samples considered in Figure 2 are shown in
368 Figure 3. As M_R and M_T are the integrated signals over all exit positions and exit angles of the
369 light at respectively the reflectance and transmittance side of the sample, the similarity relation
370 is valid and scattering can be described very accurately with only μ_s ' (Prahl, 2010; Tuchin,
371 2007). Accordingly, the 2 groups that could be observed from the μ_s ' spectra [Figure 2(c)] also
372 appear in the M_R and M_T spectra [Figure 3(a) and (b)]. Consequently, the overall levels of the
373 M_R and M_T spectra do not correlate well with the fat content of the samples. As μ_s is dominant
374 over μ_a in the Vis/NIR range for raw milk, M_U is primarily influenced by μ_s . This can be clearly

375 observed in Figure 3(c). Moreover, as the M_U spectra are presented on a logarithmic scale, the
376 plotted M_U spectra are very close to the inverse of the μ_s spectra [Figure 2(a)]. As a result, the
377 3 fat-content groups also clearly appear in the M_U spectra.

378

379 ***Relation between bulk optical properties and composition of raw milk***

380 The fat globules and casein micelles are both important absorbing and scattering
381 components in milk. Consequently, the correlation (R) between the content of milk fat and
382 casein of all 60 samples [Table 1], and the measured μ_a and μ_s values have been calculated at
383 each of the considered wavelengths [Figure 4]. High positive correlation coefficients of 0.751
384 and 0.632 – 0.762 were found between the fat content (% v/v) and the μ_a at 1220 and 1740 –
385 1770 nm. These are most likely related to respectively the second and first overtone stretch-
386 vibrations of the CH_2 -bonds (Šašić and Ozaki, 2000). Moreover, a negative correlation ($R = -$
387 0.616) was found between the fat content and the water absorption at 1450 nm. As fat is an
388 important part of the dry matter in milk, a negative correlation with the water content is obvious.
389 The positive correlation ($R \geq 0.4$) between the fat content and μ_a from 700 until 1100 nm cannot
390 be attributed to the absorption by fat. Moreover, it might be caused by the small cross-talk
391 between μ_s and μ_a [Figure 1(a) Detail], as the correlation between the fat content and μ_s in that
392 range is relatively high ($R \geq 0.839$) [Figure 4(b)].

393 Positive correlations of 0.378, 0.157 – 0.202 and 0.228 – 0.452 were found between the
394 casein content (% v/v) and μ_a at 1250, 1580 – 1620 and 1670 – 1860 nm. These absorption
395 peaks are probably related to respectively the first overtone of amide A + amide II vibrations,
396 the overlapping first overtone of amide A and amide B vibrations and the first overtone stretch-
397 vibrations of the CH -bonds in the protein side chains (Czarnik-Matusiewicz et al., 1999). Similar
398 to fat, casein followed a negative correlation ($R = -0.252$) with the water absorption at 1450 nm
399 and an overall positive correlation with μ_a from 700 until 1100 nm. The latter might also be

400 explained as cross-talk from μ_s to μ_a , as in this wavelength range, μ_s has a considerable positive
401 correlation ($R \geq 0.389$) with the casein content [Figure 4(b)]. Around 650 nm, the correlation
402 between μ_a and both the fat and casein content drops, because the variability in μ_a at these
403 wavelengths is mainly caused by a varying preservative concentration. Compared to milk fat,
404 the casein content has an overall weaker correlation with μ_a , which can be explained by the
405 smaller variability of crude protein in the analyzed milk samples [Table 1]. As the absorption
406 peaks of fat, protein, water and/or other milk components overlap, it is not possible to get a
407 perfect correlation between the absorption at a single wavelength and the concentration of a
408 milk component. Combination of the absorption information present at different wavelengths
409 through the use of multivariate calibration techniques could help to overcome this ‘selectivity
410 problem’. Since nearly no scattering effects are present in the μ_a spectra, accurate prediction
411 models could potentially be built on these data without the need for empirical scatter
412 corrections. Moreover, changes in the scattering properties would have (nearly) no impact on
413 μ_a such that the predictions are expected to be robust.

414 In Figure 4(b) the correlation between the μ_s spectra and both the fat and casein content
415 in raw milk is shown. An overall high positive correlation ($R \geq 0.766$) with the fat content (%
416 v/v) was found, with the highest correlation ($R \geq 0.975$) in the 1300 to 1400 nm wavelength
417 range. The very high correlation in the 1300 to 1400 nm region is probably because the size of
418 the fat globules in raw milk has the least impact on μ_s at those wavelengths [Figure 2(a)].
419 Accordingly, μ_s will be more dependent on the fat content itself. For radiation wavelengths
420 outside the 1300 – 1400 nm range, the size of the fat globules clearly affects μ_s , resulting in a
421 lower correlation with the fat content itself.

422 A much lower correlation ($R = 0.276 - 0.556$) was found between the casein content (%
423 v/v) and μ_s [Figure 4(b)]. This is probably because casein micelles contribute less to the light
424 scattering in the Vis/NIR range (Aernouts et al., 2015; Bogomolov et al., 2012). The correlation,

425 however, increased with decreasing wavelength. Because casein micelles are small (10 – 500
426 nm) compared to the radiation wavelengths (550 – 1900 nm), the μ_s spectrum of casein micelles
427 increases exponentially with decreasing wavelength towards the ultraviolet (UV) (Aernouts et
428 al., 2015). Moreover, as the native fat globules in raw milk have a size (0.1 – 10 μm) similar to
429 the radiation wavelengths, scattering increases with decreasing wavelength towards a maximum
430 in the Vis/NIR, followed by a decrease towards the UV [Figure 2(a)]. As a result, the
431 contribution of casein to the μ_s spectrum of raw milk increases for decreasing wavelengths in
432 the UV/Vis, which confirms the correlations in Figure 4(b). These observations are supported
433 by the findings from other Vis/NIR scattering experiments on raw milk (Kucheryavskiy et al.,
434 2014; Bogomolov et al., 2013; Bogomolov and Melenteva, 2013; Bogomolov et al., 2012;
435 Dahm, 2013). Moreover, it was found that scattering of raw milk at Vis wavelengths near the
436 UV are more related to the casein content, while a better relation with the fat content was
437 obtained towards the NIR.

438 In Figure 5, the relation between the fat content and μ_s at 3 radiation wavelengths (600,
439 1300 and 1700 nm) is provided. The solid lines in represent the linear fit between the fat content
440 for all 60 raw milk samples and the respective μ_s at each of the 3 considered wavelengths. A
441 poor correlation was found at 600 nm, while it was superior around 1300 nm. This was already
442 clearly indicated in Figure 4(b). The fitted linear lines (solid) generally overestimate the μ_s at
443 low (< 4% v/v) and high fat concentrations (> 8% v/v). This indicates that the relation between
444 μ_s and the fat content is probably not linear, resulting from the effect of dependent scattering
445 (Aernouts et al., 2014; Gaygadzhiev et al., 2008; Alexander et al., 2002). An earlier study on
446 milk (Aernouts et al., 2015) showed that there was no significant effect of dependent scattering
447 on the Vis/NIR μ_s spectra of raw milk if the fat content was below 3 – 4% (v/v). For these raw
448 milk samples, the individual scattering processes will be independent and μ_s is expected to
449 follow a linear increase with increasing fat content if the fat globule size is constant.

450 Nevertheless, if the fat content is above 4%, the scattering fat globules are close enough to
451 influence the scattering by a neighboring fat globule. This generally results in a reduction of
452 the bulk scattering coefficient spectra relative to those expected from the linear independent
453 scattering relations (Aernouts et al., 2014; Gaygadzhiev et al., 2008; Alexander et al., 2002;
454 Aernouts et al., 2015). To illustrate the effect of dependent scattering, a second linear curve
455 (dashed line) was fitted between the μ_s and the fat content for the raw milk samples with 4%
456 (v/v) fat or less [Figure 5]. Compared to the solid line (all data), the dashed line (independent
457 scattering) resulted in a consistently higher slope. Moreover, the linear independent scattering
458 fit (dashed line) generally overestimates the μ_s for fat contents above 4 – 5% (v/v), while this
459 effect increases with increasing fat content (Aernouts et al., 2014; Gaygadzhiev et al., 2008;
460 Alexander et al., 2002; Aernouts et al., 2015). At 600 nm wavelength, the difference between
461 the slopes of the two linear fits is the largest [Figure 5 (a)]. This is probably related to the
462 increased variability in μ_s for fixed fat contents [Figure 2(a)], additional to the effect of
463 dependent scattering. Moreover, the increased variation is likely due to the effect of a varying
464 fat globule size on μ_s , which is maximal for radiation wavelengths below 1100 nm [Figure 2(a)].
465 Accordingly, the effect of dependent scattering on the difference between slopes is inferior at
466 these wavelengths.

467 As the effect of dependent scattering on μ_s is clearly present in the data [Figure 5], a
468 non-linear model, taking into account this effect, would likely result in an improved fit with the
469 data of μ_s versus the fat content (Aernouts et al., 2014; Gaygadzhiev et al., 2008; Alexander et
470 al., 2002). Consequently, measurement of the μ_s at a single wavelength around 1300 nm could
471 result in very accurate prediction of the fat content in raw milk samples.

472 The offset of the linear independent scattering fit (dashed line) gives the estimated
473 average μ_s spectrum of these samples if no fat globules would be present [Figure 6].
474 Consequently, it relates to the average μ_s spectrum of the casein fraction in the raw milk

475 samples. In Figure 6, this offset is illustrated in function of the wavelength. Additionally, also
476 the μ_s spectrum simulated for the casein fraction in a bulk milk sample (fat and crude protein
477 content of respectively 4.52 and 2.65% v/v), as obtained from a previous study (Aernouts et al.,
478 2015), was plotted. Although the offset-spectrum is the result of a fitting procedure on many
479 diverse samples with a variable casein content [Table 1], there is a fairly good agreement
480 between both curves.

481 CONCLUSION

482 The visible (Vis) and near-infrared (NIR) bulk optical properties of a set of 60 raw milk
483 samples representative for milk from Flemish Holstein-Friesian cows have been measured on a
484 double integrating spheres and unscattered transmittance setup. The variation in the absorption
485 coefficient spectra was found to be clearly related to the composition of the milk samples, with
486 clear influences of the water, fat and casein content. The bulk scattering coefficient spectra were
487 found to be primarily influenced by the quantity and the size of the fat globules. A higher fat
488 content results in an overall increase, while smaller fat globules produce steeper Vis/NIR bulk
489 scattering coefficient spectra. Accordingly, the observed variation in the Vis/NIR bulk
490 scattering coefficients was large. In the 1300 – 1400 nm wavelength range, the effect of the fat
491 globule size on the bulk scattering coefficient of raw milk was found to be minimal, resulting
492 in a strong positive correlation ($R \geq 0.975$) with the fat content. Moreover, the contribution of
493 the fat content to the bulk scattering coefficient reduced towards the ultraviolet (UV), while the
494 impact of the casein content increased. This could indicate the potential of UV scattering
495 measurements for estimation of the casein content in raw milk. The anisotropy factor, on the
496 other hand, is mainly influenced by the size of the fat globules and is nearly independent of the
497 particle quantity. Moreover, larger milk fat globules cause more forward scattering of NIR light,
498 which is represented by a higher anisotropy factor. As the fat and casein content had no

499 noticeable impact on the anisotropy factor, the variation in the anisotropy factor spectra of raw
500 milk samples was rather limited.

501 The obtained information on the BOP of milk can be consulted in simulation studies to
502 improve the insight in Vis/NIR light propagation in milk and other types of emulsions, which
503 is essential for the optimal design of a Vis/NIR spectroscopic sensor that can accurately monitor
504 the quality of raw milk. Moreover, this study indicates that, for the extraction of fat globule size
505 from the scattering properties, a good separation between the bulk scattering coefficients and
506 the anisotropy factors is essential. This can only be achieved with accurate unscattered
507 transmittance measurements or multiple diffuse reflectance and/or diffuse transmittance
508 measurements close to the point of illumination. Unscattered transmittance measurements of
509 undiluted raw milk is, however, very challenging as very thin path lengths ($< 200\ \mu\text{m}$) are
510 required, the detector should be installed far ($> 1\ \text{m}$) behind the sample and the unscattered
511 transmittance signals are relatively weak. On the other hand, a small source-detector distance
512 in diffuse reflectance and/or diffuse transmittance measurements results in a reduced
513 penetration depth. Accordingly the minimal distance is limited as the sampled volume should
514 be representative for the entire sample.

515 **ACKNOWLEDGEMENTS**

516 Ben Aernouts was funded as Ph. D. fellow of the Research Foundation-Flanders (FWO,
517 grant 11A4813N). Rodrigo Watté, Robbe Van Beers and Tjebbe Huybrechts are funded by the
518 Institute for the Promotion of Innovation through Science and Technology in Flanders (IWT-
519 Flanders, respectively grants 101552, 131777 and 121611). The authors gratefully acknowledge
520 IWT-Flanders for the financial support through the GlucoSens project (SB-090053).

- 522 Aernouts, B., R. Van Beers, R. Watté, T. Huybrechts, J. Jordens, D. Vermeulen, T.
523 Van Gerven, J. Lammertyn, and W. Saeys. 2015. Effect of ultrasonic homogenization on the
524 Vis/NIR bulk optical properties of milk: measurements and simulations. *Colloids Surf. B*
525 *Biointerfaces*. 126:510–519.
- 526 Aernouts, B., R. Van Beers, R. Watté, J. Lammertyn, and W. Saeys. 2014. Dependent
527 scattering in intralipid phantoms in the 600–1850 nm range. *Opt. Express*. 22:6086–6098.
- 528 Aernouts, B., E. Polshin, J. Lammertyn, and W. Saeys. 2011. Visible and near-infrared
529 spectroscopic analysis of raw milk for cow health monitoring: reflectance or transmittance? *J.*
530 *Dairy Sci*. 94:5315–5329.
- 531 Aernouts, B., E. Zamora-Rojas, R. Van Beers, R. Watté, L. Wang, M. Tsuta, J.
532 Lammertyn, and W. Saeys. 2013. Supercontinuum laser based optical characterization of
533 turbid media in the 500–2250 nm range. *Opt. Express*. 21:32450–32467.
- 534 Alexander, M., L.F. Rojas-Ochoa, M. Leser, and P. Schurtenberger. 2002. Structure,
535 dynamics, and optical properties of concentrated milk suspensions: an analogy to hard-sphere
536 liquids. *J. Colloid Interface Sci*. 253:35–46.
- 537 Bogomolov, A., S. Dietrich, B. Boldrini, and R.W. Kessler. 2012. Quantitative
538 determination of fat and total protein in milk based on visible light scatter. *Food Chem*.
539 134:412–418.
- 540 Bogomolov, A., and A. Melenteva. 2013. Scatter-based quantitative spectroscopic
541 analysis of milk fat and total protein in the region 400–1100nm in the presence of fat globule
542 size variability. *Chemom. Intell. Lab. Syst*. 126:129–139.
- 543 Bogomolov, A., A. Melenteva, and D. Dahm. 2013. Technical note: Fat globule size
544 effect on visible and shortwave near infrared spectra of milk. *J. Near Infrared Spectrosc*.
545 21:435–440.
- 546 Cabassi, G., M. Profaizer, L. Marinoni, N. Rizzi, and T. Cattaneo. 2013. Estimation of
547 fat globule size distribution in milk using an inverse light scattering model in the near infrared
548 region. *J. Near Infrared Spectrosc*. 21:359–373.
- 549 Cattaneo, T., G. Cabassi, M. Profaizer, and R. Giangiacomo. 2009. Contribution of
550 light scattering to near infrared absorption in milk. *J. Near Infrared Spectrosc*. 17:337–343.
- 551 Cen, H., R. Lu, and K. Dolan. 2010. Optimization of inverse algorithm for estimating
552 the optical properties of biological materials using spatially-resolved diffuse reflectance.
553 *Inverse Probl. Sci. Eng*. 18:853–872.
- 554 Czarnik-Matusiewicz, B., K. Murayama, R. Tsenkova, and Y. Ozaki. 1999. of near-
555 infrared spectra of complicated biological fluids by two-dimensional correlation spectroscopy:
556 protein and fat concentration-dependent spectral changes of milk. *Appl. Spectrosc*. 53:1582–
557 1594.

- 558 Dahm, D. 2013. Review: Explaining some light scattering properties of milk using
559 representative layer theory. *J. Near Infrared Spectrosc.* 21:323–339.
- 560 Erwin, R.E., and H.E. Randolph. 1975. Influence of mastitis on properties of milk. XI.
561 Fat globule membrane. *J. Dairy Sci.* 58:9–12.
- 562 Forsbäck, L., H. Lindmark-Månsson, A. Andrén, M. Akerstedt, L. Andréa, and K.
563 Svennersten-Sjaunja. 2010. Day-to-day variation in milk yield and milk composition at the
564 udder-quarter level. *J. Dairy Sci.* 93:3569–3577.
- 565 Forsbäck, L., H. Lindmark-Månsson, A. Andrén, M. Akerstedt, and K. Svennersten-
566 Sjaunja. 2009. Udder quarter milk composition at different levels of somatic cell count in cow
567 composite milk. *Animal.* 3:710–717.
- 568 Friggens, N.C., C. Ridder, and P. Løvendahl. 2007. On the use of milk composition
569 measures to predict the energy balance of dairy cows. *J. Dairy Sci.* 90:5453–5467.
- 570 Frisvad, J.R., N.J. Christensen, and H.W. Jensen. 2007. Computing the scattering
571 properties of participating media using Lorenz-Mie theory. *ACM Trans. Graph.* 26:60.
- 572 Gamm, U.A., S.C. Kanick, H.J.C.M. Sterenborg, D.J. Robinson, and A. Amelink.
573 2011. Measurement of tissue scattering properties using multi-diameter single fiber
574 reflectance spectroscopy: in silico sensitivity analysis. *Biomed. Opt. Express.* 2:3150–3166.
- 575 Gaygadhiev, Z., M. Corredig, and M. Alexander. 2008. Diffusing wave spectroscopy
576 study of the colloidal interactions occurring between casein micelles and emulsion droplets:
577 comparison to hard-sphere behavior. *Langmuir.* 24:3794–3800.
- 578 Hamann, J., and V. Krömker. 1997. Potential of specific milk composition variables
579 for cow health management. *Livest. Prod. Sci.* 48:201–208.
- 580 ISO (International Organization for Standardization). 2000. Whole milk—
581 Determination of milk fat, protein and lactose content—Guidance on the operation of mid-
582 infrared instruments. International Standard ISO 9622:2000/IDF 141C:2000. International
583 Dairy Federation, Brussels, Belgium.
- 584 Kanick, S.C., V. Krishnaswamy, U. a Gamm, H.J.C.M. Sterenborg, D.J. Robinson, a
585 Amelink, and B.W. Pogue. 2012. Scattering phase function spectrum makes reflectance
586 spectrum measured from Intralipid phantoms and tissue sensitive to the device detection
587 geometry. *Biomed. Opt. Express.* 3:1086–100.
- 588 Kaniyamattam, K., and A. De Vries. 2014. Agreement between milk fat, protein, and
589 lactose observations collected from the Dairy Herd Improvement Association (DHIA) and a
590 real-time milk analyzer. *J. Dairy Sci.* 97:2896–2908.
- 591 Katz, G., Z. Schmilovitz, E. Maltz, M.I. Kutscher, M. Sarig, I. Halachmi, A. Hoffman,
592 H. Egozi, and E. Unar, inventors. 2003. Spectroscopic fluid analyzer. Kibutz Afikim (IL),
593 assignee. US Pat. No. 2003/0098969A1.

- 594 Katz, G., O. Shapira, L. Lemberskiy-Kuzin, and N. Pinsky, inventors. 2011. System
595 and method for on-line analysis and sorting of milk coagulation properties. S.A.E. Afikim
596 Milking System Agricultural Cooperative L.td, Kibutz Afikim (IL), assignee. US Pat. No.
597 8,072,596 B2.
- 598 Khankin, D., S. Mordechai, and S. Mark. 2012. Optimization Efficiency of Monte
599 Carlo Simulation Tool for Evanescent Wave Spectroscopy Fiber-Optic Probe. *Adv. Opt.*
600 *Technol.* 2012:1–5.
- 601 Kienle, A., F.K. Forster, and R. Hibst. 2001. Influence of the phase function on
602 determination of the optical properties of biological tissue by spatially resolved reflectance.
603 *Opt. Lett.* 26:1571–1573.
- 604 Kucheryavskiy, S., A. Melenteva, and A. Bogomolov. 2014. Determination of fat and
605 total protein content in milk using conventional digital imaging. *Talanta.* 121:144–152.
- 606 Liu, Q., and N. Ramanujam. 2006. Sequential estimation of optical properties of a
607 two-layered epithelial tissue model from depth-resolved ultraviolet-visible diffuse reflectance
608 spectra. *Appl. Opt.* 45:4776–4790.
- 609 Logan, A., M. Auldish, J. Greenwood, and L. Day. 2014. Natural variation of bovine
610 milk fat globule size within a herd. *J. Dairy Sci.* 97:4072–4082.
- 611 Løvendahl, P., C. Ridder, and N.C. Friggens. 2010. Limits to prediction of energy
612 balance from milk composition measures at individual cow level. *J. Dairy Sci.* 93:1998–2006.
- 613 Luo, Y., H. Cui, X. Gu, R. Liu, and K. Xu. 2005. Determination of optimal source-
614 detector separation in measuring chromophores in layered tissue with diffuse reflectance.
615 *Chinese Opt. Lett.* 3:659–661.
- 616 McDowell, A. K. R. 1968. Fat testing of composite Milk samples with the Milko-
617 tester. *J. Dairy Res.* 35:181–189.
- 618 Melfsen, A., E. Hartung, and A. Haeussermann. 2012. Potential of individual cow
619 scatter correction for an improved accuracy of near infrared milk composition analysis. *J.*
620 *Near Infrared Spectrosc.* 20:477–482.
- 621 Melfsen, A., E. Hartung, and A. Haeussermann. 2013. Robustness of near-infrared
622 calibration models for the prediction of milk constituents during the milking process. *J. Dairy*
623 *R.* 80:103–112.
- 624 Michalski, M.-C., B. Camier, V. Briard, N. Leconte, J.-Y. Gassi, H. Goudédranche, F.
625 Michel, and J. Fauquant. 2004. The size of native milk fat globules affects physico-chemical
626 and functional properties of Emmental cheese. *Lait.* 84:343–358.
- 627 Michalski, M.-C., J.-Y. Gassi, M.-H. Famelart, N. Leconte, B. Camier, F. Michel, and
628 V. Briard-Bion. 2003. The size of native milk fat globules affects physico-chemical and
629 sensory properties of Camembert cheese. *Lait.* 83:131–143.

- 630 Mizuno, K., M. Hatsuno, K. Aikawa, H. Takeichi, T. Himi, A. Kaneko, K. Kodaira, H.
631 Takahashi, and K. Itabashi. 2012. Mastitis is associated with IL-6 levels and milk fat globule
632 size in breast milk. *J. Hum. Lact.* 28:529–534.
- 633 Mulligan, F.J., L. O’Grady, D. a Rice, and M.L. Doherty. 2006. A herd health
634 approach to dairy cow nutrition and production diseases of the transition cow. *Anim. Reprod.*
635 *Sci.* 96:331–353.
- 636 Nielsen, N.I., T. Larsen, M. Bjerring, and K.L. Ingvarsen. 2005. Quarter health,
637 milking interval, and sampling time during milking affect the concentration of milk
638 constituents. *J. Dairy Sci.* 88:3186–3200.
- 639 Palmer, G., and N. Ramanujam. 2007. Use of genetic algorithms to optimize fiber
640 optic probe design for the extraction of tissue optical properties. *IEEE Trans. Biomed. Eng.*
641 54:1533–1535.
- 642 Pinsky, N., G. Katz, B. Sabbah, M.I. Kutscher, M. Sarig, Z. Merchav, and A. Gilboa,
643 inventors. 2013. System and method for analyzing fluids. Afikim Agricultural Cooperative
644 L.td., Kibutz Afikim (IL), assignee. US Pat. No. 8,446,582 B2.
- 645 Prah, S.A. 2010. Everything I think you should know about inverse adding-doubling.
646 Accessed Dec. 20, 2014. <http://omlc.ogi.edu/software/iad/iad-3-9-10.zip>.
- 647 Šašić, S., and Y. Ozaki. 2000. Band assignment of near-infrared spectra of milk by use
648 of partial least-squares regression. *Appl. Spectrosc.* 54:1327–1338.
- 649 Schenkel, P., R. Samudrala, and J. Hinrichs. 2013. Thermo-physical properties of
650 semi-hard cheese made with different fat fractions: Influence of melting point and fat globule
651 size. *Int. Dairy J.* 30:79–87.
- 652 Sharma, D., A. Agrawal, L.S. Matchette, and T.J. Pfefer. 2006. Evaluation of a
653 fiberoptic-based system for measurement of optical properties in highly attenuating turbid
654 media. *Biomed. Eng. Online.* 5:49.
- 655 Sharma, S., and S. Banerjee. 2003. Role of approximate phase functions in Monte
656 Carlo simulation of light propagation in tissues. *J. Opt. A Pure Appl. Opt.* 5:294–302.
- 657 Steponavičius, R., and S. Thennadil. 2009. Extraction of chemical information of
658 suspensions using radiative transfer theory to remove multiple scattering effects: application
659 to a model two-component system. *Anal. Chem.* 81:7713–7723.
- 660 Steponavičius, R., and S.N. Thennadil. 2011. Extraction of chemical information of
661 suspensions using radiative transfer theory to remove multiple scattering effects: application
662 to a model multicomponent system. *Anal. Chem.* 83:1931–1937.
- 663 Steponavičius, R., and S.N. Thennadil. 2013. Full Correction of Scattering Effects by
664 Using the Radiative Transfer Theory for Improved Quantitative Analysis of Absorbing
665 Species in Suspensions. *Appl. Spectrosc.* 67:526–535.

- 666 Tuchin, V. V. 2007. *Tissue Optics: Light Scattering Methods and Instruments for*
667 *Medical Diagnosis*. 2nd ed. SPIE Press, Washington, USA.
- 668 Vangroenweghe, F., H. Dosogne, and C. Burvenich. 2002. Composition and milk cell
669 characteristics in quarter milk fractions of dairy cows with low cell count. *Vet. J.* 164:254–
670 260.
- 671 Walstra, P., and R. Jenness. 1984. *Dairy Chemistry and Physics*. John Wiley and Sons,
672 New York, USA.
- 673 Walstra, P., J. Wouters, and T. Geurts. 2006. *Dairy Science and Technology*. 2nd ed.
674 Taylor & Francis Group, Boca Raton, USA.
- 675 Watté, R., B. Aernouts, and W. Saeys. 2012. A multilayer Monte Carlo method with
676 free phase function choice. *Proc. SPIE*. 8429:84290S.
- 677 Zamora-Rojas, E., A. Garrido-Varo, B. Aernouts, D. Pérez-Marín, W. Saeys, Y.
678 Yamada, and J.E. Guerrero-Ginel. 2014. Understanding Near-Infrared Radiation Propagation
679 in Pig Skin Reflectance Measurements. *Innov. Food Sci. Emerg. Technol.* 22:137–146.

FIGURE TEXT

680
681
682
683
684
685
686
687
688
689
690
691
692
693
694
695
696
697
698
699
700
701

Figure 1: The mean, mean \pm standard deviation (SD), minimum (Min) and maximum (Max) values for the bulk optical properties for 60 raw milk samples in the 550 – 1900 nm wavelength range: (a) bulk absorption coefficient μ_a ; (b) bulk scattering coefficient μ_s ; (c) anisotropy factor g ; and (d) reduced scattering coefficient μ_s' .

Figure 2: The bulk scattering properties for 6 raw milk samples with a nearly constant crude protein content (2.36 – 2.49% v/v) and a varying fat content (% v/v in legend): (a) bulk scattering coefficient μ_s ; (b) anisotropy factor g ; and (c) the reduced scattering coefficient μ_s' .

Figure 3: The measured (a) diffuse reflectance M_R , (b) total transmittance M_T and (c) unscattered transmittance spectra M_U for 6 raw milk samples with a nearly constant crude protein content (2.36 – 2.49% v/v) and a varying fat content (% v/v in legend).

Figure 4: Correlation (R) between the content of milk fat and casein and (a) the bulk absorption coefficient μ_a and (b) the bulk scattering coefficient μ_s in function of the radiation wavelength.

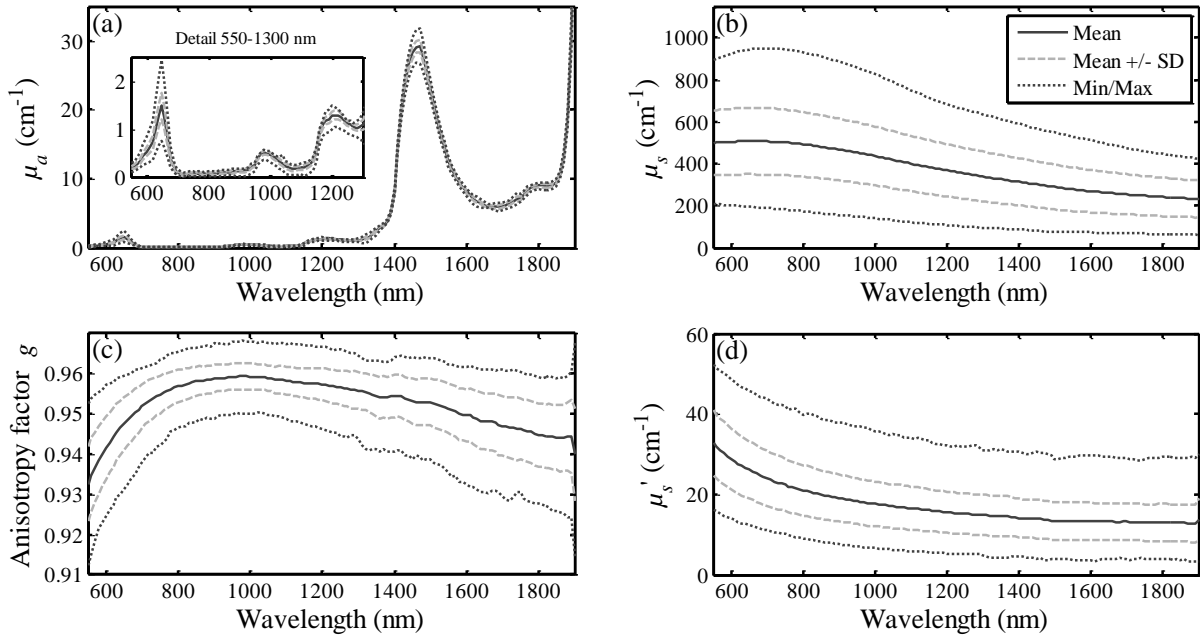
Figure 5: Scatterplots of fat content (% v/v) versus the bulk scattering coefficient μ_s at (a) 600 nm, (b) 1300 nm and (c) 1700 nm. A linear curve is fitted to all the data points (solid lined) and to the data points for which the fat content was below or equal to 4% (v/v) (dashed line).

Figure 6: Simulated (*) μ_s spectrum for casein micelle fraction (2% v/v) in raw milk (Aernouts et al., 2015) and spectrum of offset values for the linear fit between the bulk scattering coefficient (μ_s) spectra and the fat content for samples with a fat content below 4% (v/v).

702

FIGURES

703 Figure 1

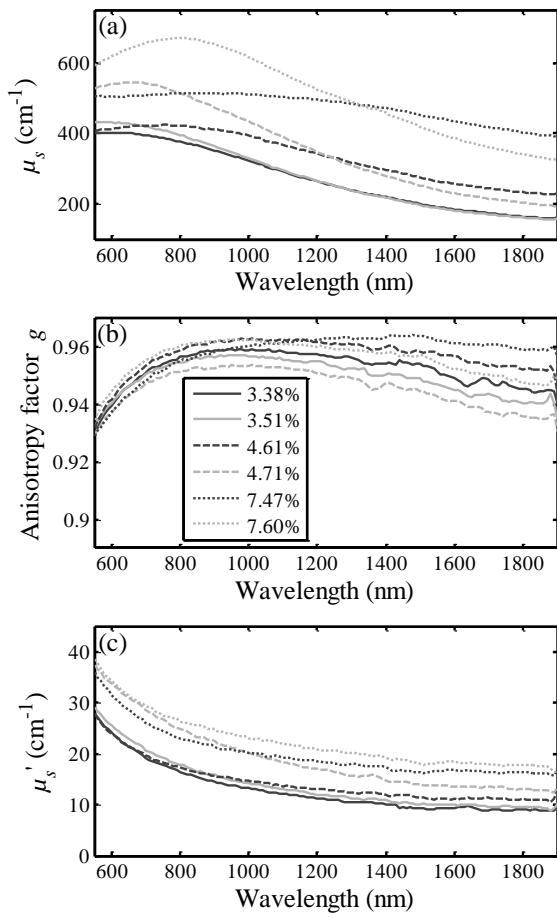


704

705

Aernouts: figure 1

706 Figure 2

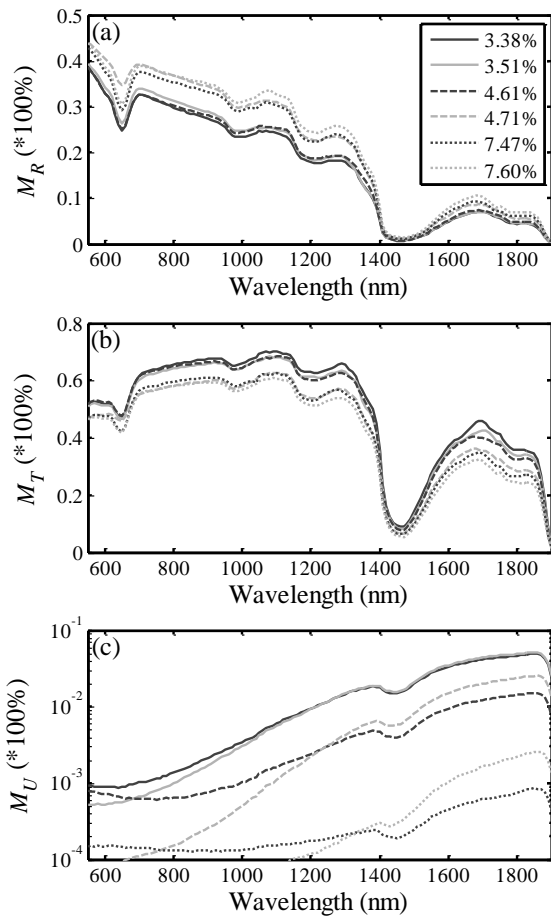


707

708

Aernouts: figure 2

709 Figure 3

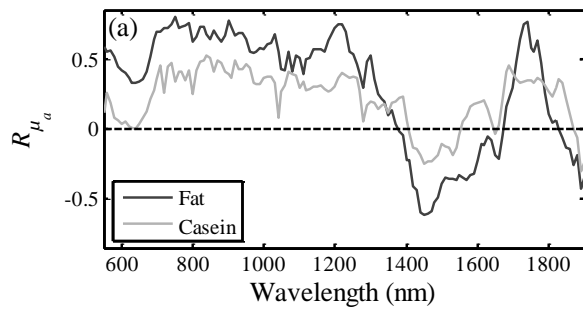


710

711

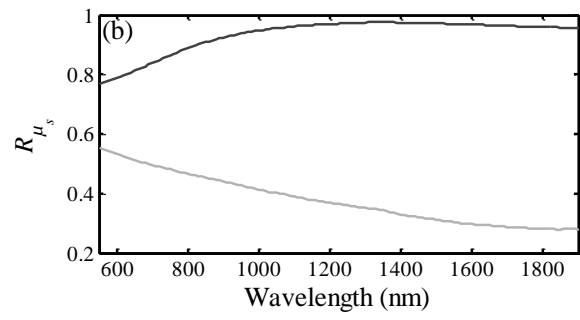
Aernouts: figure 3

712 Figure 4



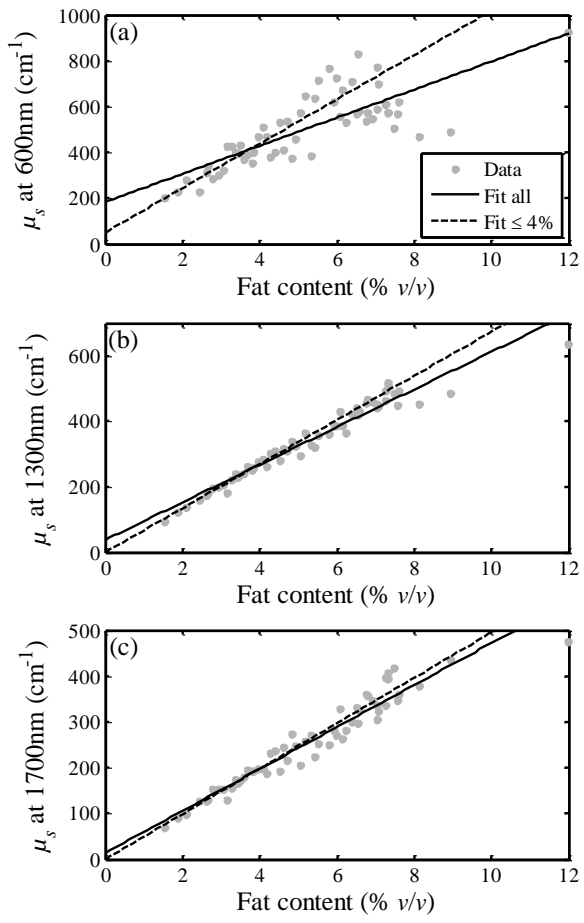
713

714



Aernouts: figure 4

715 Figure 5



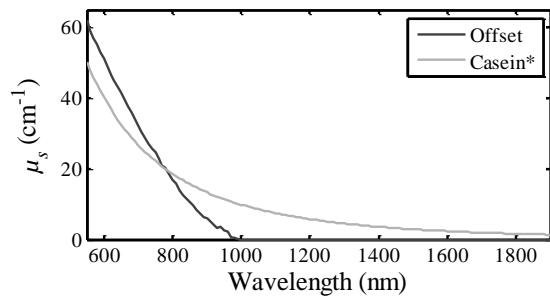
716

717

718

Aernouts: figure 5

719 Figure 6



720

721

Aernouts: figure 6

722

TABLES

723 Table 1 Basic statistics (all % v/v) on the main components in the 60 consulted raw milk
724 samples.

725

726

727

Component	Mean	SD	Min	Max
Fat	5.24	2.01	1.52	12.0
Crude protein	2.72	0.424	2.09	3.73
Casein	2.05	0.424	1.58	2.82

728

729

730

731

732

733

734

735

736

737

738

