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# Relating Surface Electromyograms of the Facial Muscles During Mastication to the Mechanical and Sensory Properties of Foodstuffs

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## 1. Introduction

Surface Electromyography (sEMG) has been widely used for studying human mastication, due to its ability to non-invasively monitor the activity of muscle groups associated with chewing (Boyar & Kilcast, 1986; Brown, 1994). It is regarded as the “gold standard” for objective measurement of simple parameters relating to chewing behaviour, such as chew rate and strength. Attempts have been made to approach a quantitative analysis of the sEMG signals, in terms of mechanical action on foods (Agrawal et al., 1998; Braxton et al., 1996; Brown et al., 1996, 1998; Horio & Kawamura, 1989; Mioche & Martin, 1998; Wilson & Brown, 1997; Yven et al., 2010). sEMG has been used to identify differences in chewing patterns between individuals, and to classify them into groups according to their chewing efficiency (Blissett et al., 2006; González et al., 2002; Lassauzay et al., 2000).

There is also interest in using sEMG data in studies of sensory texture (Duizer et al., 1996; Lee et al., 2009; Mathoniere et al., 2000; Mioche, 2004; Peng et al., 2002; Sun et al., 2001; Yven et al., 2010). Thus sEMG of the masticatory muscles provides a potential link between physical or mechanical properties of foodstuffs, and sensory evaluations, in particular of texture, made by consumers.

In this chapter we present the hardware and software needed to conduct sEMG of facial muscles during mastication, and describe the signal that is acquired, as well as options for further data treatment of this signal to obtain quantities that can be analysed by statistical means (Section 1). We highlight some of the issues that may be encountered downstream, in particular arising from the variability associated with the technique, especially between-volunteer and between-session variance (Section 2). We show that with judicious data scaling (Section 2.4), sEMG can be linked to mechanical and sensory properties of food (Section 3). Throughout, we use examples of our own data, collected during a series of related projects carried out at the Institute of Food Research in Norwich.

### 1.1 Collecting sEMG signals from mastication

To obtain sEMG signals from the masticatory muscles, disposable surface electrodes are attached in pairs to the surface of the skin above the masseter and temporal muscle groups, on both sides of the face (figure 1). The muscular action potentials (MUAPs) associated with chewing actions (the sum of which effectively constitutes the signal that is recorded) are

small and require amplification, typically using a polygraph. The outputs from the amplifier are passed to an analogue-to-digital converter (ADC), generally operating at a sampling rate of 1kHz, and captured by a PC. The resulting signal from each electrode is a time-varying response representing each muscle group's bioelectrical activity for the duration of the chewing episode.

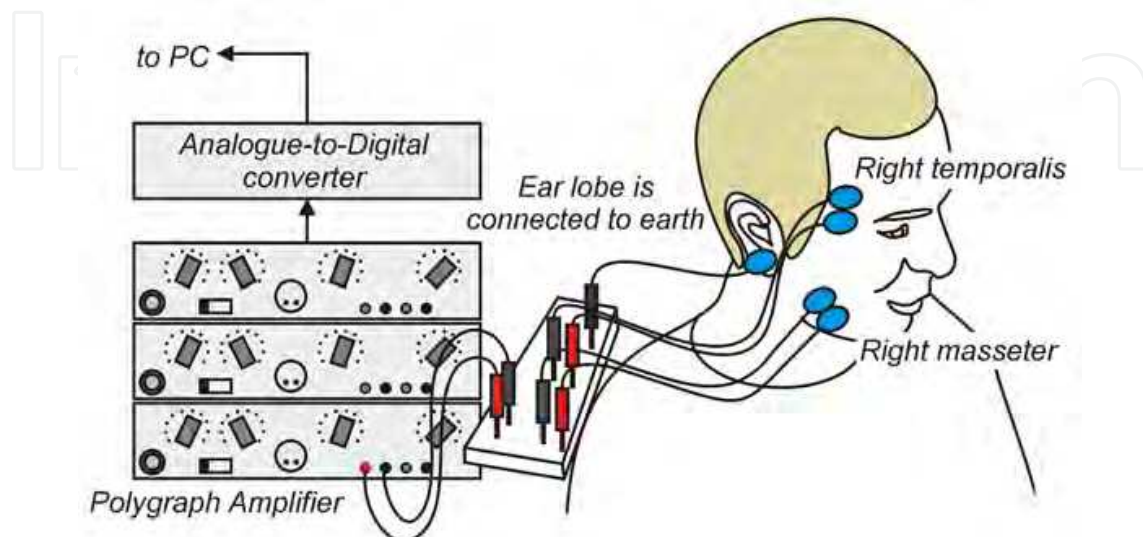


Fig. 1. Diagram showing a volunteer ready for sEMG recording of mastication. It is useful to take photographs of each volunteer once they are wired up, to assist in reducing inter-session variability.

The data presented throughout this chapter were collected using equipment as follows: bipolar disposable electrodes (Blue Sensor A-50-VS, Medicotest, Ølstykke, Denmark); a polygraph amplifier (model 7E, Grass Instrument Co., Massachusetts, USA); and an ADC interface (model 1401plus, Cambridge Electronic Design Ltd., Cambridge, UK). Data were logged by connecting the ADC to a desktop personal computer running the Spike2 data collection software package (Cambridge Electronic Design Ltd., Cambridge, UK). All subsequent signal processing was carried out in Matlab (The Mathworks, Cambridge, UK) installed with the Statistics Toolbox.

## 1.2 Time-domain sEMG signals – the electromyograms

Typical signals from two electrode channels (right temporalis and right masseter) obtained from a volunteer consuming one bite of apple are shown in figure 2. The main features are indicated. The first bite and subsequent chews appear as large, regularly spaced features, and these arise from the gross movements of the masticatory muscles. The end of chewing is marked by a swallow, which can be seen fairly clearly in these particular sEMG signals. However, swallow movements are not always distinctive (Hodgson et al., 2003), and we have on occasion found it useful to provide a “swallow indicator” device to be operated by the volunteer, so that the moment of swallowing is precisely located in time (Sprunt et al., 2002). Note the correspondence between the activities of the temporalis and masseter muscle groups. For normal, healthy chewing behaviour, there is involvement of both these muscle groups to similar extents. Likewise, a degree of correspondence is found between the right and left electrode channels.

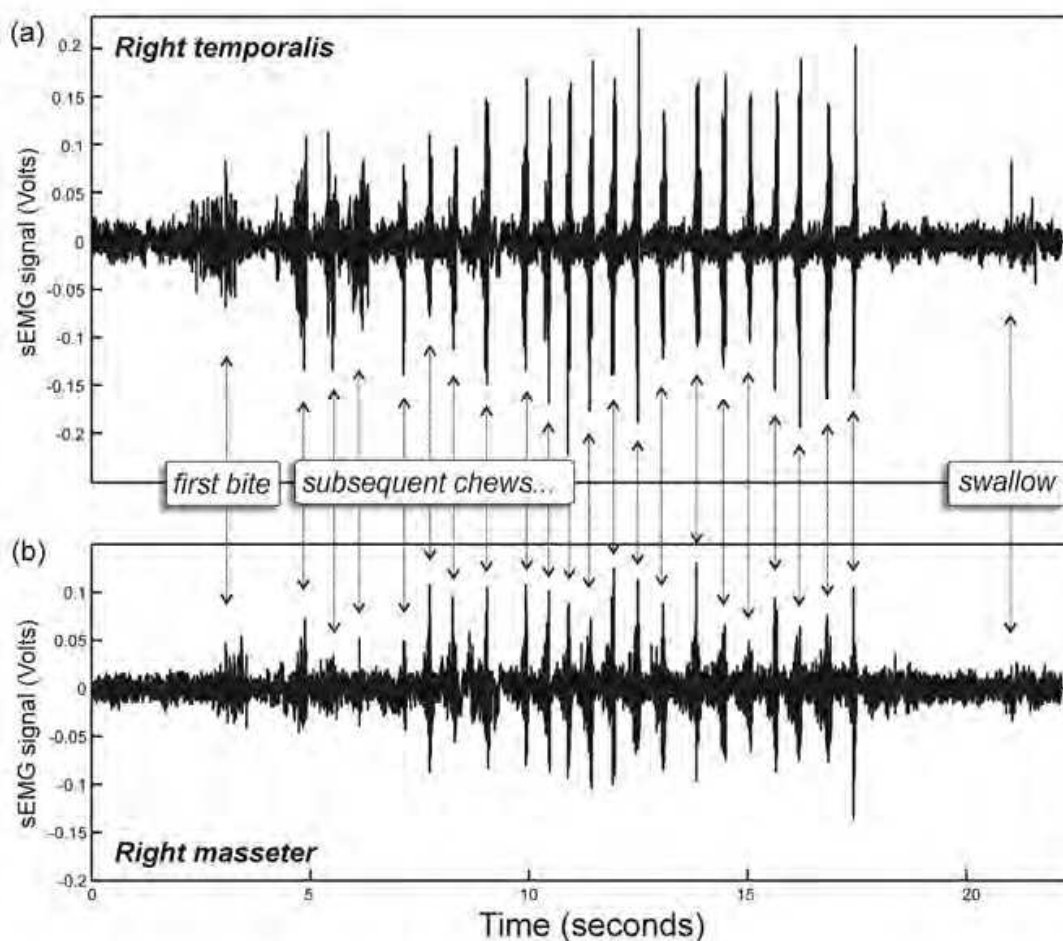


Fig. 2. Data from the right temporalis and right masseter channels from a volunteer consuming one bite of apple. The main features are marked. Note the equivalent vertical scales – in this example, the temporalis muscle group produced slightly larger signals, although there is clearly substantive involvement of both muscle groups. This is typical of normal chewing behaviour.

Depending on the food being consumed and the purpose of the study, sEMG readings may be collected over periods of up to several minutes. Consequently the amount of raw data produced can be very large. Until relatively recently, complete raw measurements have been too difficult to handle on standard desktop computers. Researchers have of necessity analysed only simplified forms of this data, such as the chew interval and rate. Figure 3 illustrates the principle by which these values are extracted from the sEMG signals. The reduction in complexity and size of the dataset is substantial: from 80,000 data points in the raw signals shown here, to a few tens of extracted values and summary statistics. Much of the literature examines how these extracted quantities relate to the properties of the food being consumed (Blisset et al., 2006; Braxton et al., 1996; Brown, 1994; Brown & Braxton, 2000; Brown et al., 1996, 1998; Duizer et al., 1996; Lee et al., 2009; Plesh et al., 1986; Tornberg et al., 1985; Veyrune & Mioche, 2000; Yven et al., 2010). However, as the power of computer processors continues to increase, so does the capacity to handle larger amounts of data, and more recently, researchers have begun to utilise the whole signal. The majority of our sEMG work has adopted this kind of approach, introduced in the following section.

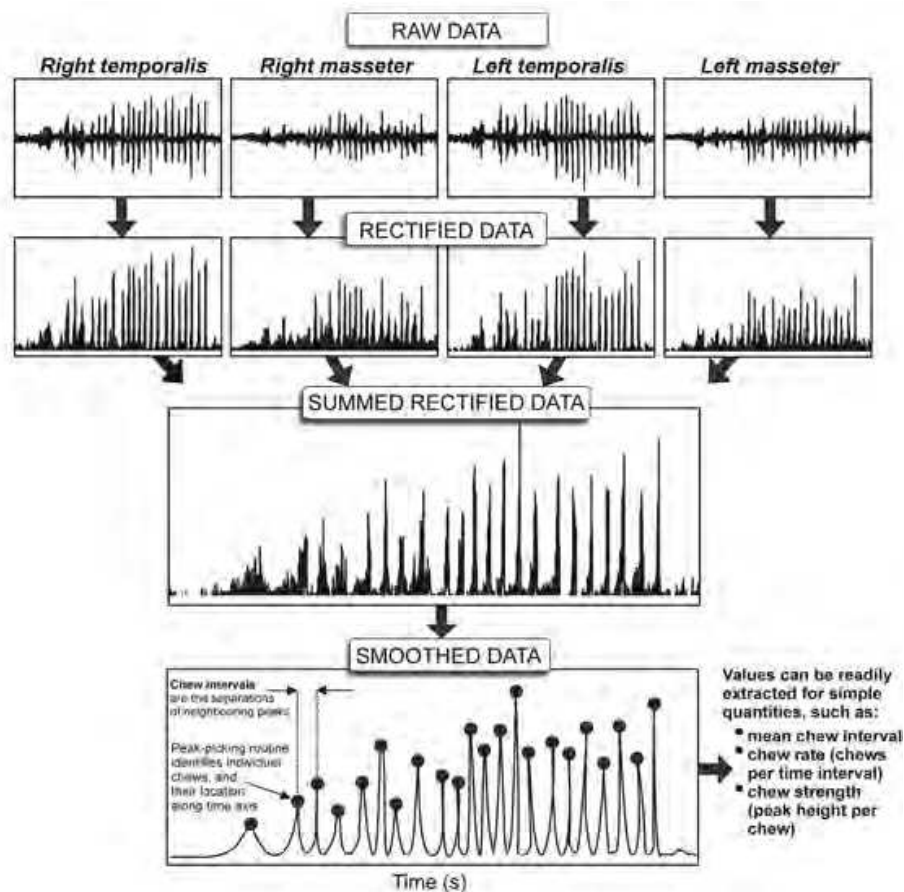


Fig. 3. Extracting parameters from the raw electromyograms.

### 1.3 Frequency domain signals – the power spectra

Electromyograms are collected in the time-domain, as measurements of a response as a function of time. The mathematical procedure of Fourier transformation can be used to express these readings instead as a function of frequency. The fast Fourier transform (FFT) algorithm operates on a digitized time-domain signal, sampled at a rate  $v$ , to produce a frequency-domain spectrum, in which the maximum frequency that can be detected is  $v/2$  (a consequence of the Nyquist sampling theorem). The square of the amplitude of the Fourier-transformed signal is known as the power spectrum.

Fourier transformation has been applied to sEMG signals in the past, with the mean frequency being the most often used derived parameter as it has been found to relate to muscle fatigue (see review in Al-Mulla et al., 2011) and has also been shown to be linked to the proportions of different fiber types (Yuen et al., 1989). However there may be more subtle, frequency-specific information in the sEMG signals that can be exploited. To access this information, one needs to look separately at bands of frequencies (Schumann et al., 1994) or at the power spectrum itself (Subasi, 2006). Indeed in our own work we have investigated whether different regions of the power spectrum can be related to other data types collected during the experiment. One of the main advantages of working in the frequency domain is that registering (aligning) several electromyograms across different episodes of chewing becomes straightforward. This is because the range of the frequency scale is related solely to the ADC sampling rate. There is no need for the electromyograms to match with regard to the start or the end of recording, nor to even contain the same number



of data values (a process called “zero filling” can be used to force a match between readings). All that is required is that the signals were collected at the same sampling rate. A consequence of the inherently small electrical signals measured in sEMG is that the electromyograms, as well as the resulting power spectra, invariably contain unwanted noise arising from the electronics in the amplifier and ADC. It is useful, therefore, to improve the signal-to-noise ratio (SNR) as far as possible through signal averaging or “co-adding” of replicate measurements. Precisely what constitutes a “replicate” is an issue that needs some consideration. For example, we noted above that the electromyograms from the different electrode pairs produce highly correlated signals, and these individual signals could be co-added in the frequency-domain to improve the SNR. Another method of increasing the SNR is to co-add power spectra from successive time windows; overlapping time windows can also be used (in effect, a “moving average” smoothing process). These methods are illustrated in figure 4. The proviso is that the signal-averaging method should be consistent with the aims of the study. For instance, the window method is appropriate if there is no specific requirement to study muscle activity as a function of time; co-adding different electrode channels is appropriate if there is no desire to study the different muscle groups separately.

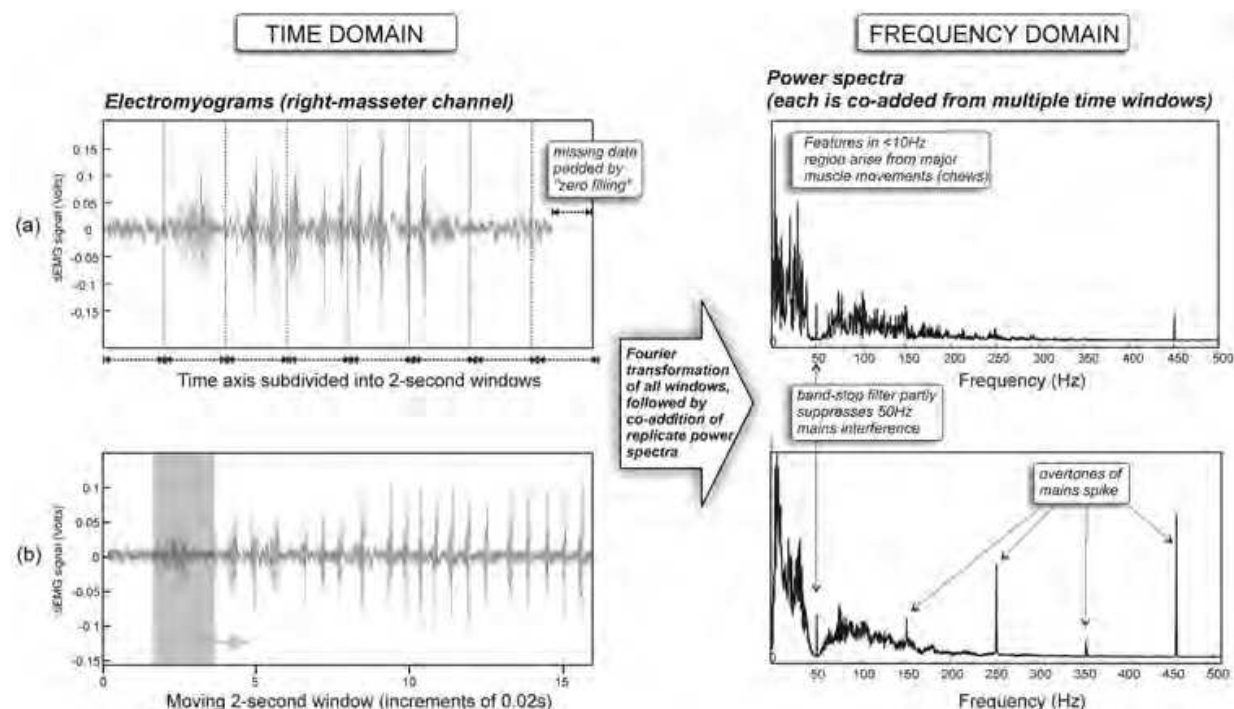


Fig. 4. Signal-averaging using windows in the time-domain. The electromyograms on the left side of the figure were collected from one electrode channel, and two different episodes of chewing. The power spectra on the right side of the figure were calculated from the electromyograms using the window method of signal-averaging. In (a), the signal was subdivided into 2-second windows (zero-filling was used to pad the last of these to give a window of the same duration). In (b), a window of 2-seconds width was “moved” along the time axis, in increments of 0.02 seconds, to effect smoothing. In both cases, all windows were Fourier transformed and the resulting spectra co-added to give a single, signal-averaged power spectrum in the frequency-domain.

Some of the main features of typical sEMG power spectra are also indicated on figure 4. The frequency scale is in Hertz, with its range determined by the ADC sampling rate. Frequency

resolution is determined by the number of data points Fourier transformed (i.e., in each electromyogram window). Features arising from the main muscle movements involved in chewing can be seen in the low-frequency region ( $\nu < 10\text{Hz}$ ). The broad depression centred at 50Hz arises from a band-stop filter present in the polygraph to suppress interference from the mains electricity supply. In some of the data, overtones of this  $\nu = 50\text{Hz}$  interference can be seen at  $\nu + 2\nu$ ,  $\nu + 4\nu$ ,... There are also some distinct features in the region 10 – 50Hz. In sEMG studies of a range of different muscle groups, these are generally attributed to synchronized activity of muscle motor units arising from rhythmic firing of the central nervous system (see for example McAuley et al., 1997, and the review of the literature included therein).

As they share a common frequency scale, power spectra can be easily collated into a matrix for processing with linear algebra techniques. This enables comparison across large collections of sEMG data, acquired for example from different volunteers, and/or from the consumption of a range of foodstuffs. This possibility is exploited extensively in different studies that will be described in the remainder of this chapter, all of which involved large collections of sEMG data from multiple volunteers. The data acquisition equipment for all studies was as described above, i.e., electromyograms were collected from four muscle groups using an ADC operating at a 1kHz sampling rate. In all cases, prior approval to conduct the study was obtained from the local ethics committee.

## 2. Between-volunteer differences in sEMG

### 2.1 A study of edible gels with characterised textural attributes

The first of the case studies comprises sEMG signals recorded from eight volunteers, who each consumed five edible gels on five separate occasions. This work formed part of a wider study on flavour release (Kemsley et al., 2002; Smith, 2004; Sprunt et al., 2002; Sprunt & Smith, 2002; Wright & Hills, 2003; Wright et al., 2003). All gels were prepared using the same nominal formulation, and then flavoured with five varying amounts of anethole. Complete details of the gel preparation and serving order can be found in Kemsley et al. (2002). Mechanical properties of the gels were determined using a TA-XT2 Texture Analyser (Stable Micro Systems, Godalming, Surrey, UK). A single-sided razor blade (length 39 mm, depth 12.5 mm, thickness 0.25 mm) was driven vertically through the gel axis at 0.05mm/sec (total travel approximately 12mm), and the work done in cutting calculated from the integrated force-distance curve.

sEMG recording was discontinued in each instance when the volunteer indicated that the gel's flavour could no longer be perceived. The minimum duration of any electromyogram was ~32 seconds. Consequently, the first 32768 ( $=2^{15}$ ) data values in each electromyogram were passed to a fast Fourier transform algorithm and converted to power spectra, each containing 16384 data values. To improve the SNR, these were summed across the four electrode channels to give a single, signal-averaged power spectrum per chewing episode.

#### 2.1.1 Visual examination of the data

From visual comparison of the sEMG signals from different volunteers, it was found that each volunteer exhibits highly characteristic chewing behaviour, and furthermore, this is broadly consistent between sessions. This is most evident from examination of the power spectra. In figure 5, two different representations of the frequency domain dataset are shown. On the left hand side, the complete matrix of [200 x 16384] data values is shown as a heatmap. Each row in this map represents a single power spectrum, and the data have been ordered such that the spectra from individual volunteers are grouped together (25 per

volunteer: five episodes of chewing at each of five sessions). Clear blocks of data can be seen, corresponding to the 25 spectra from each individual. The right hand side of the figure shows the mean power spectra, obtained by averaging across all chewing episodes and sessions for each volunteer. Again, there are clear differences between the signals for each individual, although mean spectra alone do not convey any information about the within-volunteer variation, in contrast to the heatmap view. An expansion of the low-frequency (<10Hz) region in a selection of the power spectra is shown in figure 6, highlighting some of the volunteer-specific characteristics that persist across sessions.

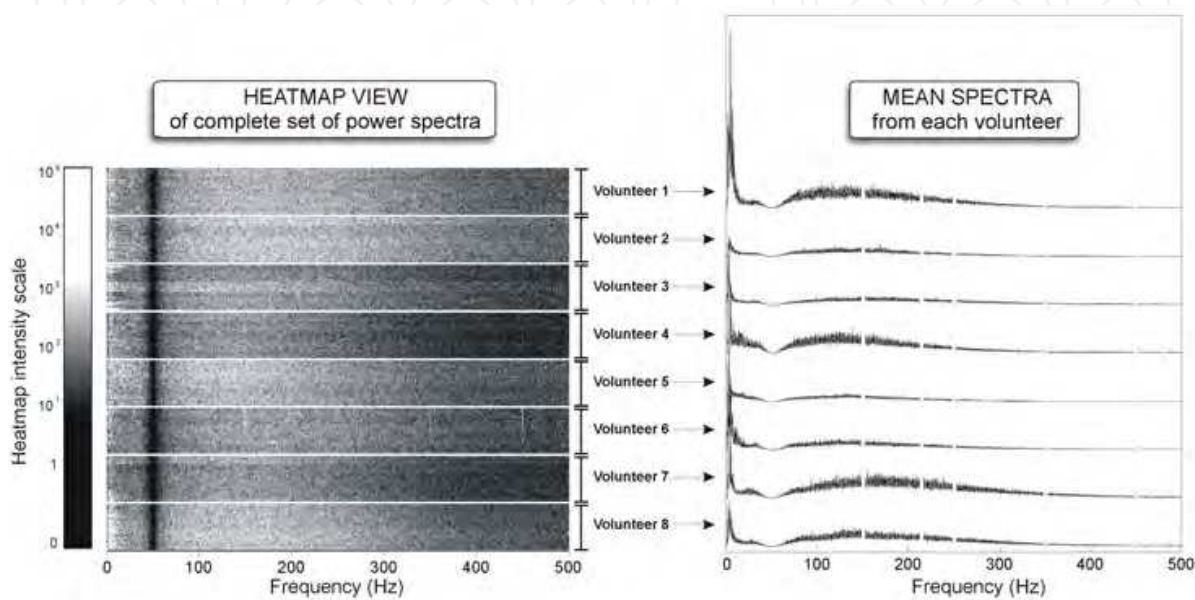


Fig. 5. Different representations of the frequency domain dataset.

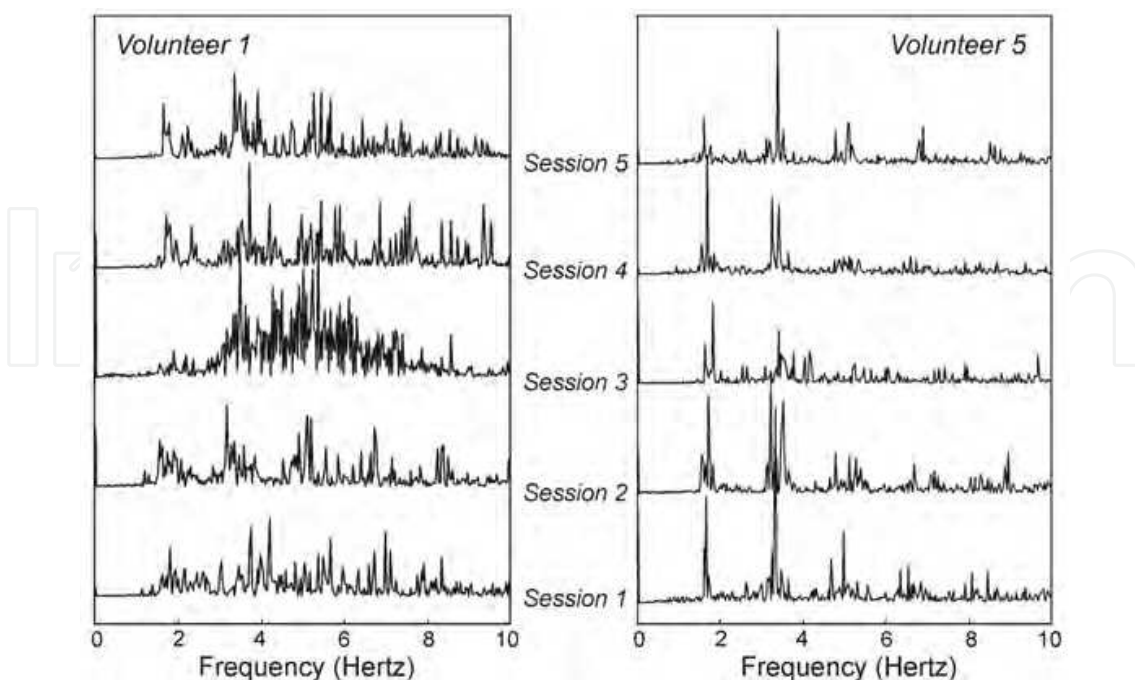


Fig. 6. An expansion of the low-frequency (<10Hz) region in a selection of the power spectra from two of the volunteers.



### 2.1.2 Multivariate analysis - PCA

An alternative and highly efficient means of viewing a large data matrix of this kind is to process it with a data compression technique such as principal component analysis (PCA) (Jolliffe, 1986; Krzanowski, 1988). This method produces a transformed matrix - the PC scores - which contains most of the information that was present in the original data matrix, but in a rearranged form. Crucially, the scores matrix is much smaller in size, making it considerably easier to examine graphically. Furthermore, the scores are ranked by their variances, thus the largest (and hopefully most interesting) sources of variation are represented in the first few scores, whilst the noise component is relegated to lower scores. The PCA transformation can thus lead to an effective increase in the SNR of the systematic information of interest.

Figure 7 shows the first two PC scores obtained from the set of power spectra, using correlation-method PCA. Together, these two scores alone account for over 25% of the information content (variance) that was present in the original data set. Each point on this plot represents a power spectrum from one episode of chewing. It can be immediately seen that there is considerable clustering of the data arising from each individual. Data from volunteers 1, 2 and 6, for example, can be completely distinguished from one another, as

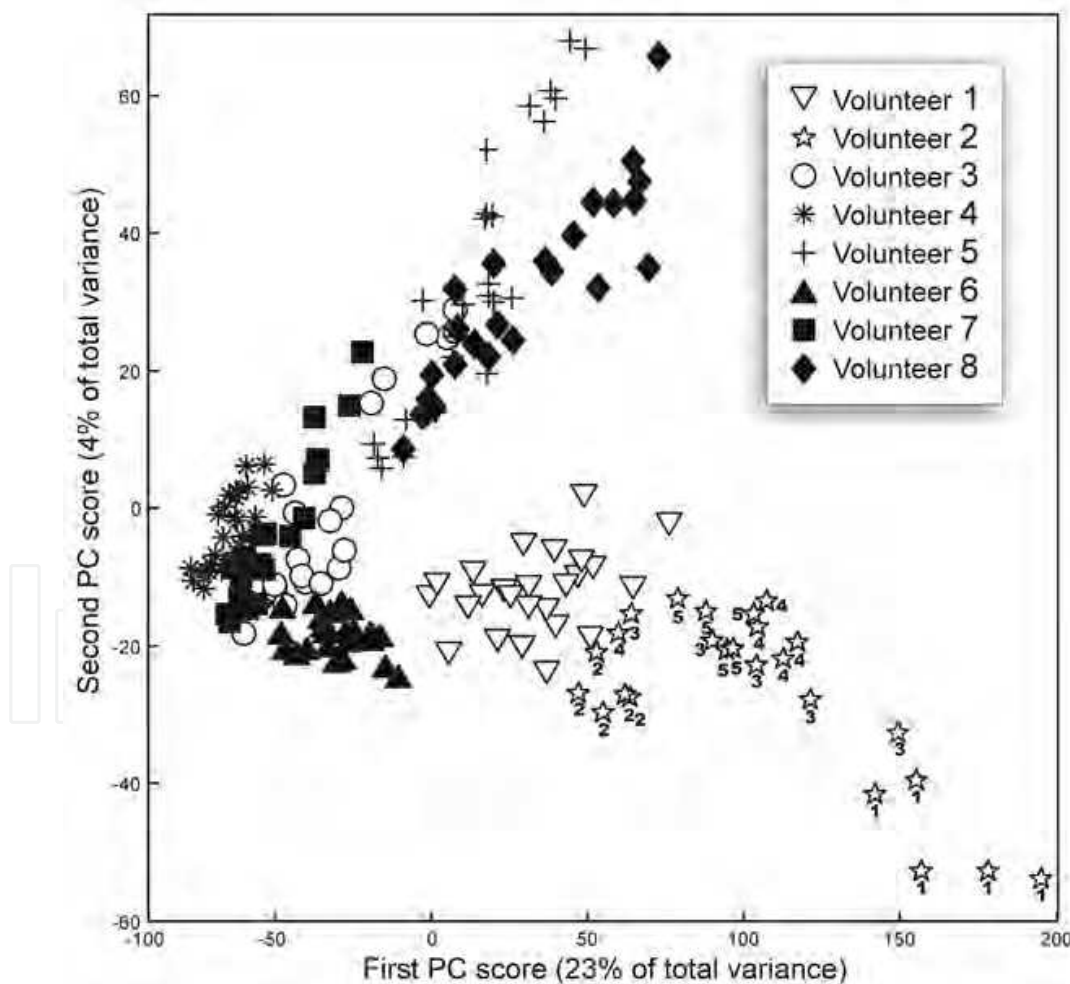


Fig. 7. PCA (correlation method) applied to sEMG power spectra from edible gels. The entire frequency range (0 - 500Hz) was used. Sessions for one volunteer (2) are marked by a number (1-5)

well as from the remaining volunteers. This is particularly remarkable considering each volunteer's data comprised measurements from five recording sessions, separated in time by periods of days. It also confirms the suggestion from qualitative examination of the spectra that volunteers can be associated with a characteristic low-frequency spectrum. Closer examination of figure 7 showed that within each volunteer's batch of signals, data from the different sessions tended to cluster together also. For clarity, this is indicated for one volunteer's readings only. Inter-session variability is likely to arise largely from irreproducibility in positioning the electrodes. This is an established source of variance in sEMG data (De Luca, 1997).

### 2.1.3 Discussion

The data collected in this study were also treated in the time-domain by Wright et al. (2003), who examined the distribution of the intervals between chews, and showed that a different distribution was obtained from each volunteer. Our multivariate treatment of the power spectra has further indicated that each single sEMG recording can be identified as originating from a distinct volunteer. In addition to the readily observed differences in the low-frequency region, there are characteristic differences between individuals' responses at higher spectral frequencies, as seen from the heatmap view. It is known that the shape of the frequency distribution changes in response to fatigue, with a shift in the median towards lower frequencies. This has been shown in both sEMG (see review in Al-Mulla et al., 2011) and vibromyography (VMG) studies (Herzog et al., 1994). However, volunteers will differ in the rate at which they become fatigued, and in the extent to which this is manifested in their sEMG signal. All of these findings suggested that when volunteers are asked to consume a foodstuff using their natural chewing behaviour, they do so in an individual, characteristic fashion.

Consistent differences between volunteers' sEMG characteristics could also be due to a variety of behavioural and anatomical factors. Individuals differ in terms of their efficiency in breaking down the food bolus, which is influenced by salivary flow rates and the ability to reform and move the bolus in the mouth. In addition, there is variation between individuals in their pattern of muscle activation, and hence in terms of the level of muscle recruitment and activation in the chewing sequence. This arises to some extent from the anatomy of the masticatory apparatus, as well as characteristics such as the muscle fibre-type construction (proportion of type I and II fibres), the fibre size and motor unit arrangement, the thickness of the subcutaneous layer and the electrical resistance of the skin (Westbury & Shaughnessy, 1987).

### 2.2 Between-volunteer differences in studies of prescribed chewing

A subsequent multi-volunteer study aimed to further explore the causes of between-volunteer variation. In particular, we sought to examine the extent to which subjectivity in sEMG signals arises from a factor potentially within the conscious control of individuals: the manner in which they chew. For this work, we dispensed with an edible stimulus (and the associated phenomena of particle breakdown and saliva stimulation). There are literature precedents for the use of model stimuli in studies of mechanical properties and sEMG responses. The use of miniature load cells was described by Mioche et al. (1993), who recorded bite forces from 25 to 124N at biting rates of 1 and 2Hz. The force-deformation behaviour of a model material, Optosil, has been compared with that of real foodstuffs by Olthoff et al. (1986). Edlund & Lamm (1980) compared sEMG signals for various foods and Optosil, and Horio & Kawamura (1989) compared sEMG signals with instrumental texture parameters for foods. There is also

precedent for the use of a metronome; Plesh et al. (1987) used sEMG and a Kinesiograph to study the jaw movements of subjects chewing gum, at individuals' preferred rates, and also at rates prescribed using a metronome.

In our study, volunteers simulated chewing by elastically deforming calibrated, spring-loaded wooden pegs held between their incisors, 5mm from the end of the peg arms. The volunteers were asked to coordinate their movements with the sound produced by a metronome, which was operated at several different, predetermined rates: 30, 60, 90 and 120 bpm (beats per minute). Each of six volunteers provided duplicate measurements at the four different rates, on three separate occasions. Mechanical characterisation of the pegs was carried out by compression in a universal test machine (Stable Micro Systems Texture Analyzer, model TA-XT2). The average work done in operating the pegs was 106 mJ measured at a compression point 5mm from the ends of the peg arms.

The raw electromyograms were collected, Fourier transformed and signal-averaged in the same way as in the work on edible gels described above, although in this instance only 30 seconds of data were retained from each reading, as some volunteers indicated fatigue after this time. In all cases, the sEMG responses were greatest on the masseter-right and masseter-left channels. This is because the use of the incisor teeth involves less activity of the temporal and more of the masseter muscles, compared to the study of freestyle chewing of gels, in which more of the facial muscles tended to be involved.

### 2.2.1 Visual examination of the low-frequency data

The low-frequency region in a selection of the power spectra are shown in figure 8, which typify the data set as a whole. Sharp peaks can be seen in the power spectra that correspond

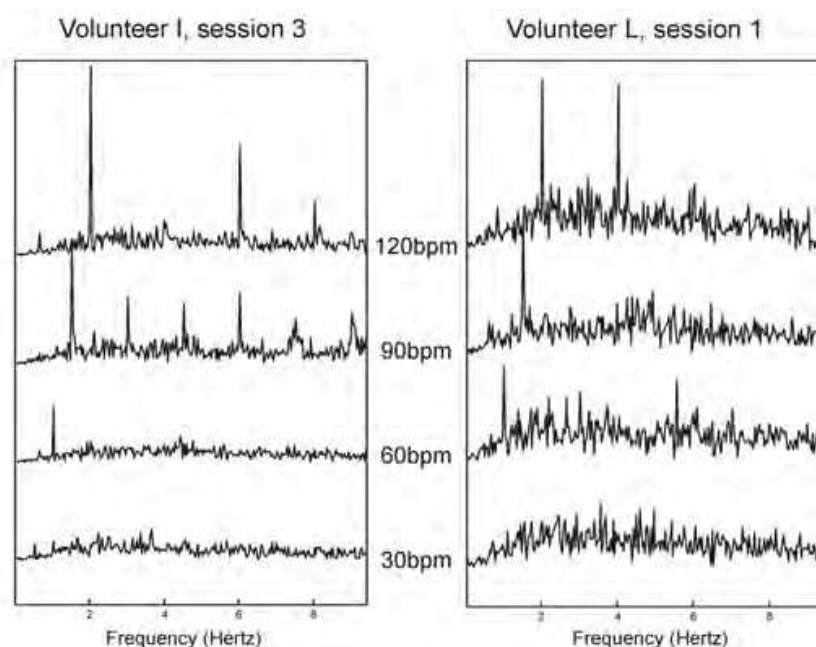


Fig. 8. Low-frequency region in spectra from prescribed chewing. For a chew rate of 120bpm, a peak is clearly seen at 2Hz, with some smaller 'overtones' at 4Hz, 6Hz,... When the chew rate is 90bpm, there are peaks at 1.5Hz with overtones at 3Hz, 4.5Hz,..., and when it is 60bpm the peaks occur at 1Hz, with overtones at 2Hz, 3Hz,... In general, volunteers found it harder to precisely coordinate their jaw movements with the lower prescribed rates. Note that no peaks are clearly seen in any volunteers' data from the chew rate of 30bpm.

directly to the prescribed chew rates. For most volunteers, this is especially clear for the chew rates of 90bpm and 120bpm. In general, volunteers appeared better able to coordinate and maintain these higher prescribed rates. These were closest to the natural chewing rhythms observed in the studies on gels (compare with figure 6).

### 2.2.2 Multivariate analysis: Focussing on different frequency ranges

In theory, this low frequency region is dominated by the features attributable to prescribed chewing only, and since the prescriptions were the same for all individuals in the study, it might be expected that this would reduce the degree to which their sEMG signals can be differentiated. An analysis of the chew interval data, analogous to that carried out by Wright et al. (2003) and reported in our paper (Kemsley et al., 2003) appears to indicate that this is so. From analysis of chew interval distributions, volunteers seemed to differ in their ability to precisely coordinate and maintain the prescribed chewing patterns, but individuals could not be identified by their chew interval readings alone. However, application of PCA to the power spectra, which is able to decompose different sources of systematic variation, shows that there is still some differentiation between volunteers. Figure 9(a) shows the first two PCs obtained from the low frequency (<10Hz) region, using the same method of analysis (correlation PCA) as in figure 7. The prescribed chew rates are indicated for one of the volunteer's data only, for reasons of clarity, along with a "direction" in this PC space that corresponds to variation in the chew rate as marked. It is apparent that there is still some separation of the signals by volunteer, even in this low-frequency region alone. Figure 9(b) shows the results of applying the same PCA method to the >10Hz region. The clustering according to volunteer is more marked. A further PCA analysis was applied to the whole frequency range (i.e. a direct analogue of figure 7); this showed even clearer clustering according to individual (figure 9(c)).

From examination of these figures, it would seem that variation between volunteers is an effect comparable in magnitude to the grossly different prescribed chew rates. The third and subsequent scores in all the PCA analyses (not shown) indicated some variances associated with chew rate, but smaller than those of PCs 1 and 2. This result is perhaps counter-intuitive: one might have anticipated that, when considering the dataset as a whole, by far the largest source of variance would be chew rate. This was, after all, a prescribed difference between conditions for obtaining the readings, the effects of which are clearly visible in the low-frequency region of the sEMG spectra.

Next, PCA was applied to the whole frequency range from each chew rate separately. The first two scores from the 120bpm dataset are shown in figure 10. There is now clear clustering and separation of the data from each volunteer. Similar results were obtained from analyses of the 90, 60 and 30bpm sets. This confirms that higher frequencies contain useful information for distinguishing volunteers, and moreover, the volunteer-specific nature of these higher frequencies is not removed by asking volunteers to constrain their chewing behaviour. In agreement with the gel study, our findings once more show that if sEMG signals are considered as a whole, then individual volunteers produce highly characteristic signals, which remain characteristic even when the manner in which they chew is highly controlled. In the context of examining properties of food materials, this must be regarded as an undesirable phenomenon.



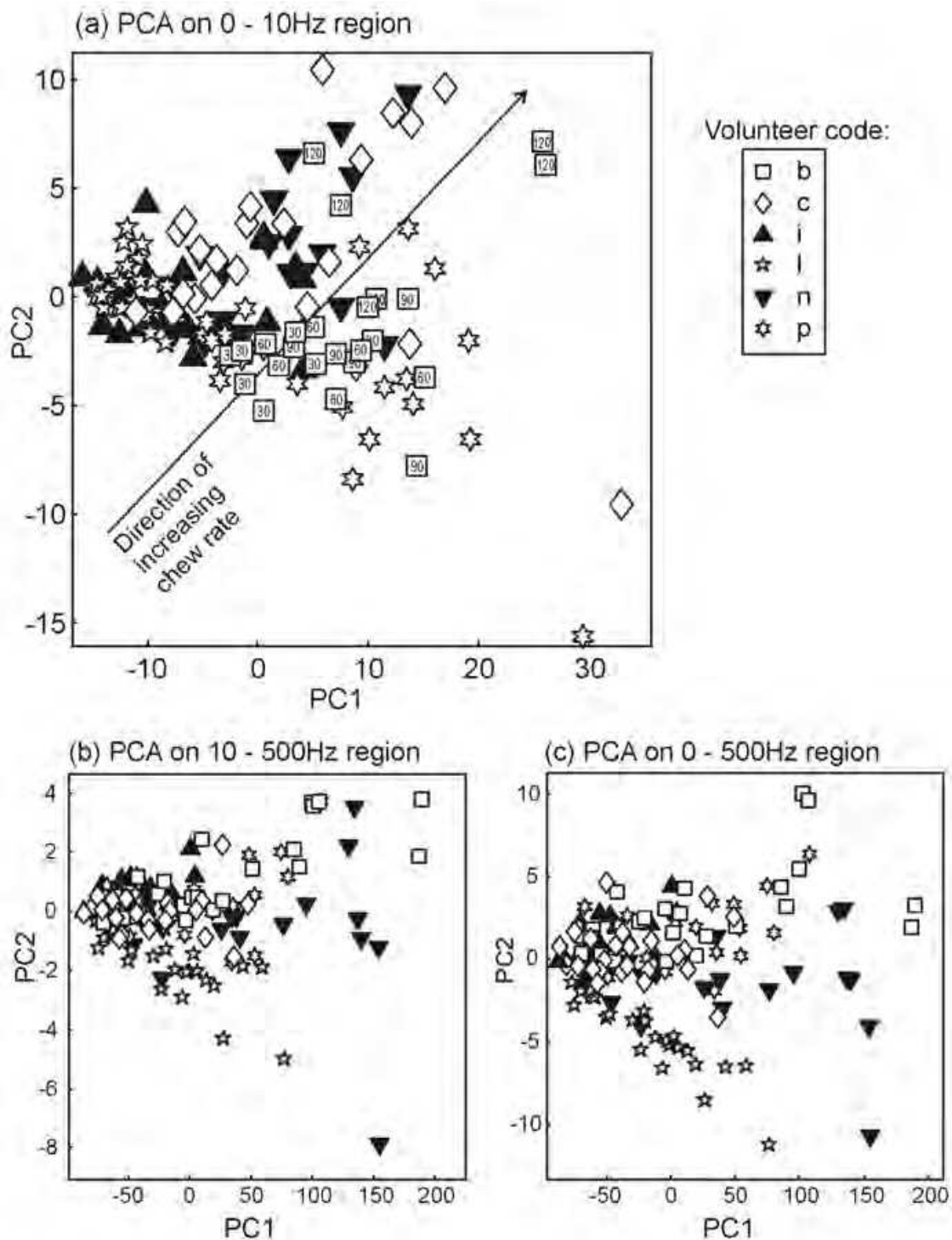


Fig. 9. PCA scores plots for different frequency ranges. In (a), one volunteer's data points are marked with the prescribed chew rate. The arrow indicates the direction in the PC space associated with the chew rate; all volunteers' data demonstrated the same directional trend. There is still noticeable grouping according to volunteer, despite the prescribed chewing behaviour. In figures (b) and (c), different regions of the power spectrum were passed to the PCA procedure; the clustering according to volunteer becomes clearer when frequencies above 10Hz are included.

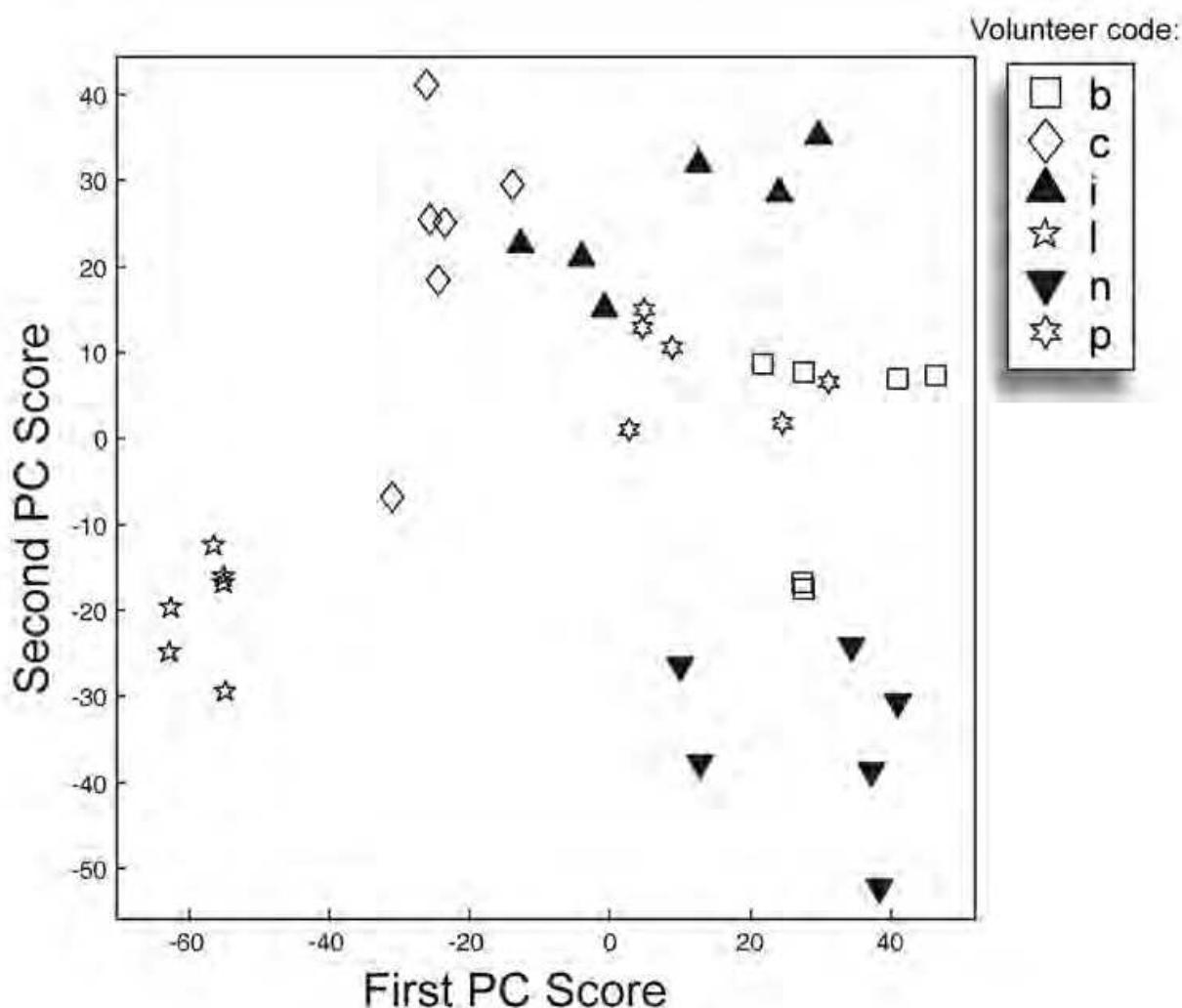


Fig. 10. PCA scores plot of first vs. second PC from the subset of data from the 120bpm chew rate only (using the whole power spectrum frequency range). Data were additionally normalized by setting the integrated spectral area to unity, before correlation-method PCA.

### 2.3 Summary: The extent of between-volunteer variance

These studies have clearly established that individuals exhibit highly characteristic sEMG spectra, and the relative between-volunteer and within-volunteer variances are such that individuals can be uniquely identified by their sEMG signature. Investigations using subsets of different regions of the frequency range showed that this characteristic nature is maintained even at frequencies higher than those associated with the gross muscle movement. The clustering according to volunteer was found irrespective of whether individuals use natural freestyle chewing behaviour, or were asked to chew in an artificial, highly prescribed manner.

This corroborates the findings from a number of other studies. For example, in a study involving five different foods, Horio & Kawamura (1989) found volunteers to differ in the way the food hardness affected their number of chewing strokes, and overall chewing time. Brown (1994) and Brown et al. (1998) observed significant between-volunteer variation for several temporal and amplitude parameters calculated from the time-domain signal (duration of the

activity burst, period between bursts of activity, duration of the chewing period, mean voltage within activity burst, maximum voltage, and area under sEMG trace); these were recorded whilst chewing a range of different food types. Volunteers have also been classified into “chewing efficiency” groups, based on the weight loss from a stick of chewing gum, and the median particle size of almonds chewed a specified number of times (Brown & Braxton, 2000, Braxton et al., 1996); when consuming other food types (meat, biscuits), these groups exhibited different behaviours (numbers of chews, total chewing time and chew work). Similarly in a study on confectionery chews, Blisset et al. (1996) characterised groups on the basis of chewing force, chewing rate, proportion of work and total number of chews, and observed that this could influence flavour release, though this was product-dependant. Mioche & Martin (1998) observed clear differences between naïve and trained volunteers, based on their sEMG burst times, chew time, duration and work, in particular in the extent to which their behaviour was modified, comparing chewing with, and without, simultaneous sensory judgment. González et al. (2002) also found that the chewing behaviour of experts (trained subjects) was influenced by the goal of the experiment more than that of untrained subjects; in addition there were differences in chewing time, chewing work and chewing rate between experts and untrained subjects, and a larger between-session variation in untrained subjects for number of chews, chewing time, mean voltage, and chewing work.

In none of these studies was it shown, however, that volunteers exhibit consistent, individually characteristic behaviour over extended periods of time. This finding is important, because it demonstrates the inherent subjectivity of sEMG as a form of measurement. This may need to be mitigated in order to explore underlying, subtle relationships between sEMG readings and material or sensory properties of the stimulus. This is an area of work that will be examined in Section 2.4 and exploited in the remainder of this chapter. Moreover, the higher frequency components of the signal are neglected in conventional analysis of sEMG data, which processes raw signals to obtain parameters such as chew intervals, chew rate, and so on. Our findings show, however,, the high frequency region clearly contains non-trivial information, since volunteers can be distinguished by their high-frequency sEMG spectra alone.

## **2.4 Data scaling to remove inter-subject and inter-session variance**

We return now to discuss the power spectra collected from the consumption of edible gels. Figure 7 showed clearly the between-session and between-volunteer variances. However, coding the symbols by the texture attributes of the gels revealed no conclusive clustering according to the textural properties (not shown); equally unfruitful was an exhaustive search of subsequent PC dimensions. However, this could simply be because any association with the textural properties is small and not clearly seen against the background of much larger volunteer and session effects.

A straightforward means of removing variation associated with both session and volunteer is to apply some form of scaling to the batches of signals from each volunteer and session. There are many different candidate scaling schemes. Here we use standardization, a well-known statistical technique which scales each variate (data values at each frequency in the power spectrum) so that they have mean of zero and a standard deviation of unity. When PCA is applied to the “batchwise” standardized data set, we can see from the plot of scores that variation associated with either the volunteer or session is removed (figure 11(a)). However, when we code the symbols by the different gels consumed, a new trend emerges – an association in the first PC dimension with the gel’s texture as measured by work done in

cutting. This is not easy to discern in the heavily populated scores plot (figure 11(b)), but much clearer when the score is plotted individually against the textural property separately (figure 12).

This amounts to strong evidence of a within-volunteer trend that associates sEMG reponse with increasing work done in cutting. We can conclude that a statistically significant association exists between the power spectra and the texture as expressed by mechanical cutting. This is an indication that quite subtle properties of foodstuffs have a discernible influence on sEMG readings; this is explored further in the subsequent section which examines data collected from a large-scale study of both the mechanical and sensory properties of apples.

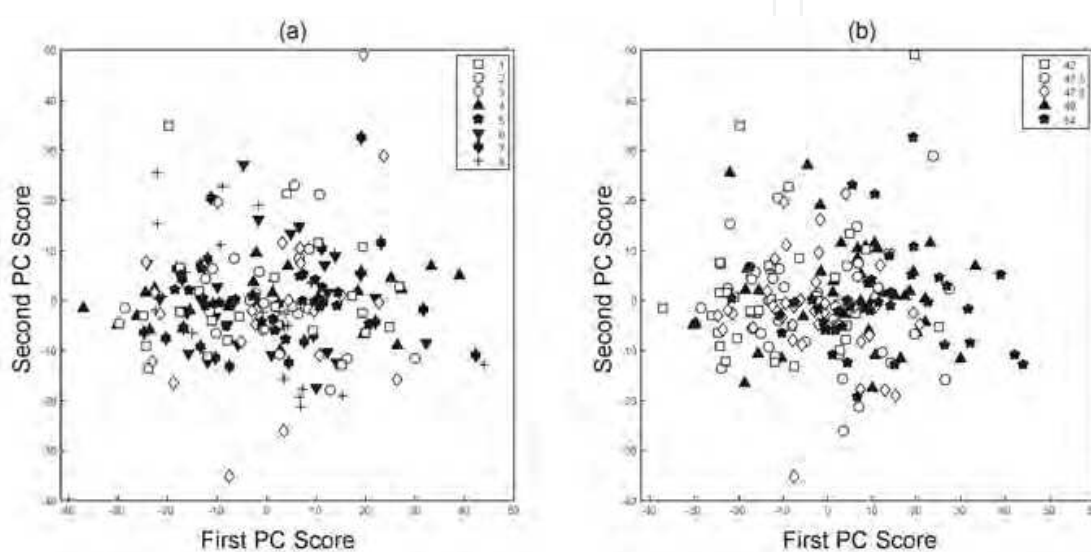


Fig. 11. PCA scores plots of “batchwise” standardized (per volunteer, per session) data set. In (a), the symbols are coded by volunteer; in (b), by edible gel. The numbers in the legend refer to the mean work done (Nmm) in cutting each of the five preparations.

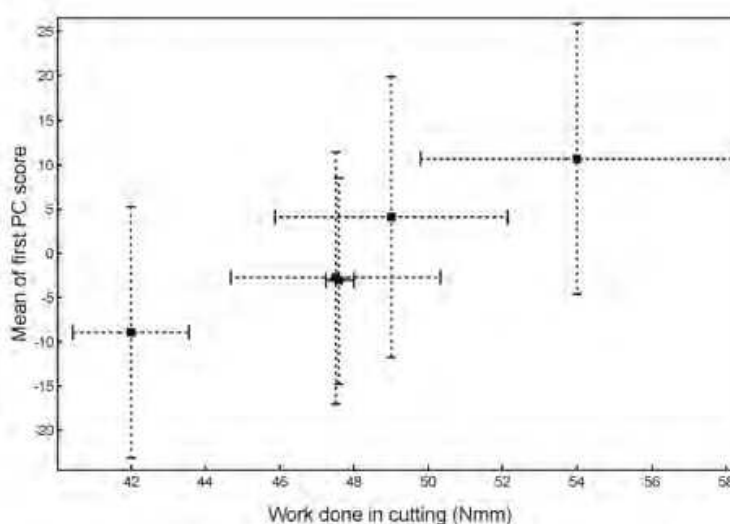


Fig. 12. Plot of gel texture (work done in cutting) versus the first PC score. Error bars represent 2 standard deviations.



### 3. Relating sEMG signals to mechanical and sensory texture in apples

The remainder of this chapter is concerned with textural properties of apples, in particular a single variety, Red Delicious, which is particularly vulnerable to quality deterioration during extended storage. In this work, sEMG was used to explore the link between mechanical and sensory measurements of various textural attributes.

As a term, “texture” is rather complex. The International Organisation for Standardisation defined texture in 1992 as “the mechanical, geometrical and surface attributes of a product perceptible by means of mechanical, tactile and where appropriate, visual and auditory receptors”. The texture of a food, then, is perceived by humans via the sense of touch from surface responses within the mouth, deep responses by muscles and tendons, and potentially also auditory cues.

The current industry standard technique for inferring textural quality in apples is the “Magness and Taylor” test. This is conducted using a penetrometer, which comprises a metal probe that punctures a hole into the fruit, and records a value indicative of the mechanical resistance. This puncture test has been used in numerous academic studies on apple texture, where it is frequently related to sensory scores (Abbott et al., 1984; Barreiro et al., 1998; Mehinagic et al., 2003). Sensory evaluations are arguably the best reference data in this regard, as it is ultimately people who decide on the quality and acceptability of foods. Among the most common sensory terms relating to texture in apples are “hardness” (or “firmness”) (Abbott et al., 1984) and “mealiness”. These attributes are highly correlated with consumer acceptance: apples with firm texture are valued (Harker et al., 2000; Péneau et al., 2006), whereas consumers dislike mealy apples, perceiving these as soft, dry, and with poor textural quality (Daillant-Spinnler et al., 1996; Jaeger et al., 1998).

In terms of objective measurements, mealiness is the most intractable. The penetrometer, for instance, is unable to predict perceived mealiness sufficiently accurately. Brett & Waldron (1996) described the cellular changes responsible for the physical condition: the cell walls thicken and the intercellular bonds become weaker. During mastication, the cells slide apart but remain whole, so the texture is sensed as soft; and because the cell contents are not as readily released in the mouth, the fruit is perceived as dry. Mealiness develops due to ripening, senescence, temperature and humidity during storage; some cultivars (such as Red Delicious) are more prone to become mealy than others.

The work discussed in this section relates sEMG, sensory evaluations and penetrometer measurements from Red Delicious apples. The data presented here are a subset taken from a larger collection of measurements obtained from an extensive, multi-stage experiment, which is reported in Ioannides (2006) and Ioannides et al. (2007). Herein we focus on two texture-related sensory terms, hardness and mealiness, obtained by classical sensory evaluation - a single assessment by the subject representing their impression of the attribute over the entire eating period (Lee & Pangborn, 1986). Mealiness in particular is detected during chewing and not from the first bite (Lillford, 2000) and so there is a need to evaluate the whole chewing episode. Andani (2000) found that sensory mealiness was detected after 4 chews, which implied that some sensory attributes may require some manipulation of the food before the attribute can be perceived. Our wider study included a further three terms, which are outlined briefly in the methods section below, and discussed in full in the journal article (Ioannides et al., 2007).

sEMG has been used extensively to examine mastication patterns in a wide range of foods, including apples (Kohyama et al., 2005). Sakamoto et al. (1989) used sEMG to examine chewing of a range of food products with widely different textural qualities; they hypothesised that sEMG may provide an objective textural assessment tool, potentially forming a bridge between instrumental and sensory tests. Relationships have subsequently been sought between sEMG data and sensory scores: Karkazis & Kossioni (1998) compared raw carrot and peeled apple, and reported significant correlation between sensory hardness and sEMG activity in the masseter muscles.

The aim of the work presented here is to expand upon these ideas, and to explore whether sEMG can improve prediction of sensory properties compared with the use of the penetrometer alone. In the long-term this may enable sEMG to assist in assessing product quality, and crucially, obviate the need for trained panellists. Brown et al. (1994) suggested that an individuals' chewing behaviour may influence their ability to discern textural differences; this idea is also considered.

### 3.1 Methods

#### 3.1.1 Samples

Red Delicious apples (*Malus domestica* 'Red Delicious') were obtained from a Washington State (USA) pack-house. All fruit were nominally the same size (grade 72) and same colour grade ("dark red not striped"). Mealiness can be forced onto fruit by storage at high humidity and temperature; thus, four storage regimes were devised to achieve a range of textures in the apples, detailed as follows:

Regime A: 4°C in refrigerator

Regime B: 1 week at 20°C (tray covered with polythene)

Regime C: 2 weeks at 20°C (tray covered with polythene)

Regime D: 4 weeks at 20°C (tray covered with polythene)

Preliminary work (Ioannides et al., 2006) had demonstrated that these regimes were able to induce a range of textural qualities in the fruit. Allocations of apples to each regime were made randomly. Immediately before measurements began, each apple was placed at 20°C for 12 hours, allowing it to equilibrate to room temperature.

#### 3.1.2 Data collection

Following a number of training sessions, each of a set of thirteen panellists attended five data collection sessions, at which apple halves were consumed as follows: two halves from the same apple, three halves from different apples (5 halves in total). Each fruit was washed and cut in half before being presented cut-face down on a plate to the panellist. The presentation order was as balanced as possible with respect to the different storage regimes, to avoid order and carry-over effects. The panellist held the apple so that the skin was facing the floor, and took a natural-sized bite for each sensory attribute. Panellists took five bites per apple half, and made sensory evaluations as follows:

Bite 1: (No sensory assessment. The panellists were told to regard this as a "practice bite" only)

Bite 2: *Hardness*, defined as the overall impression of hardness for the entire bite.

Bite 3: *Mealiness*, defined as the extent to which the sample was dry and grainy and broke down into granular pieces during chewing.

Bite 4: *Juiciness*, defined as the amount of juice released from the fruit into the mouth.

Bite 5: *Skin toughness*, defined as the overall impression of how difficult it is to bite thorough and chew up the skin especially in comparison with the flesh.

These terms were chosen as they are pertinent to consumer acceptance (Daillant-Spinnler et al., 1996), and have been used in a range of other textural studies of apples (Barreiro et al., 1998; Saftner et al. 2002). The sensory assessments were made on a continuous un-structured scale, using a handle attached to a potentiometer with a nominal range of 0 – 5 volts (Sprunt et al., 2002). Extreme reference foods were used in training to enable individuals to “calibrate” their perceptions to this scale during the training and familiarization sessions, as described in Ioannides (2006). sEMG signals were recorded from all chewing episodes, using acquisition conditions as described earlier in this chapter.

### 3.2 Puncture test measurements

The Effegi penetrometer (Alfonsine, Italy) held in a drill stand was used to perform puncture tests on each apple. A thin slice of skin was removed and the 11 mm diameter plunger was forced into the flesh up to 8 mm; the maximum resistance reached was recorded.

### 3.3 Visual inspection and exploration of the sEMG data

Mean sEMG power spectra, calculated for each subject across all sessions (125 signals per subject), are shown in figure 13(a). Most striking is the very large difference in signal intensities – approximately an order of magnitude between, for instance, subjects 51 and 60. In general, features in the spectra are common to all subjects, and indeed to the data from edible gels presented earlier in this chapter. The larger number of volunteers in the present case, however, has led to an even greater range of magnitudes in response. An estimate of the total work done over each episode of chewing can be obtained by integrating the sEMG power spectra across the available frequency range (Carson et al., 2002; Kemsley et al., 2002; Peng et al., 2002; Schumann et al., 1994). The integrated values are depicted as boxplots in figure 13(b), which illustrate the range of values obtained by volunteer. The large variation in signal intensities is reflected clearly in the differences between the medians.

Figure 14(a) shows the first vs second PC scores from the complete set of power spectra. In common with previous work, the greatest source of variation in the sEMG data is due to subject, and the secondary source of variance is session. When the standardization procedure discussed earlier (section 2.4) is applied, these two sources of systematic variance are removed, and other trends in the data can be explored. One rather unexpected grouping emerges: in many of the subjects’ data, there is clear clustering according to certain bite numbers, most noticeably Bite 5 (evaluation of skin toughness) and Bite 1 (the “practice” bite, with which no sensory evaluation was made). This is illustrated for one volunteer’s data in figure 14(b). This indicates that an unexpectedly large amount of variance in the data is associated with the bite number, or equivalently, the sensory evaluation being undertaken. Detailed statistical analysis (one-way ANOVA, reported in full in Ioannides et al., 2009) confirmed that this was a significant effect in around half of the volunteers.

This analysis shows that the instruction given to a subject (i.e., “make no sensory evaluation”, “evaluate skin toughness”) can cause the subject to modify his/her chewing

behaviour such that there is a change in the sEMG signal. Perhaps the difficulty in making certain sensory evaluations caused some subjects to alter their mastication behaviour. Similarly, it seems plausible that some subjects chew differently when they are “practising” compared with when they are making sensory evaluations. Subjects were asked to use consistent habitual chewing behaviour throughout, so this modification may represent subconscious departure from the instructions. These findings provide strong quantitative evidence for an effect that has been speculated upon in the literature. Mioche & Martin (1998) showed that patterns of mastication change depending on whether or not subjects simultaneously carry out a sensory evaluation, and particularly so in trained subjects. Zimoch & Gullett (1997) suggested that different chewing behaviours may affect textural perception. Mathevon et al. (1995) proposed that subjects may alter their chewing behaviour according to their thoughts. We concur with this suggestion, and further propose that this alteration may take place subconsciously. So, the nature of the sensory evaluation must be added to the already large number of systematic factors that affect the sEMG signal. Furthermore, where the purpose of sEMG is to assist in objectively assessing texture, then this source of variability must be regarded as a confounding factor.

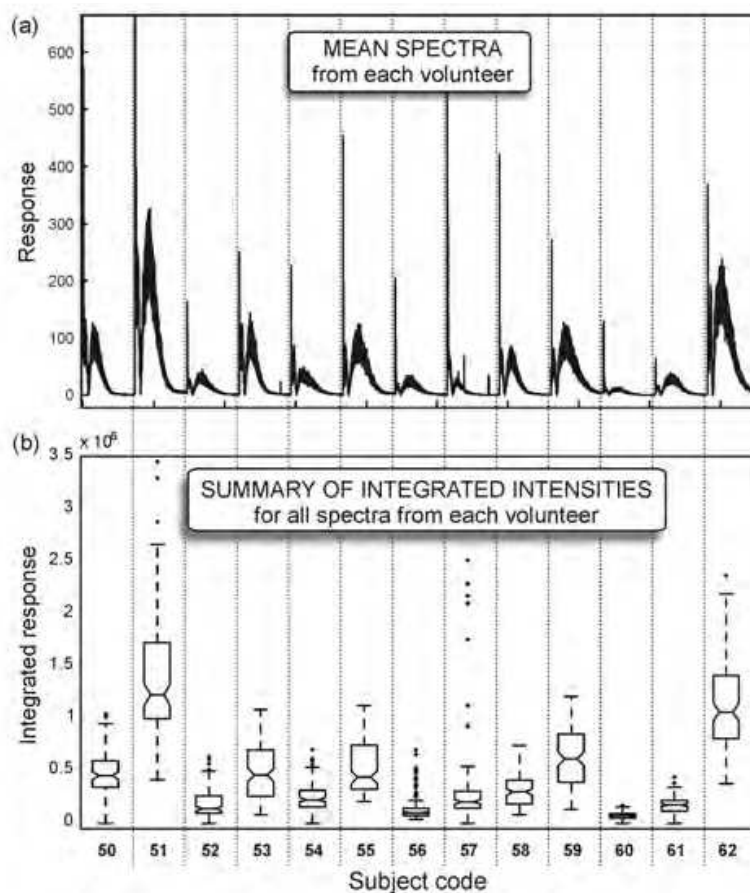


Fig. 13. (a) The mean power spectrum from each volunteer, and (b) boxplots that summarize the integrated power spectra obtained across all batches of data from each volunteer.



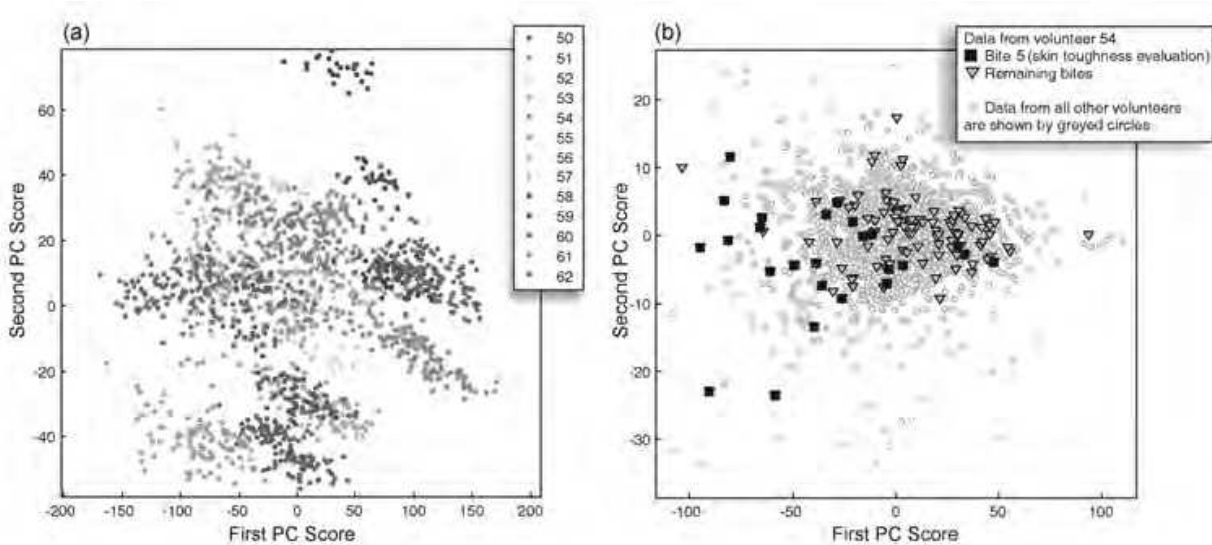


Fig. 14. (a) The first vs second PC scores (correlation method PCA, log-transformed data) from the complete set of power spectra. (b) PCA on the same original data set, but now standardized to remove volunteer and session effects. The points originating from one volunteer (54) are highlighted; data corresponding to bite 5 (= skin toughness evaluation) appears to be somewhat separated from the remaining readings.

### 3.4 Relationship between sEMG and puncture test data

It has been established that integrated sEMG signals are correlated with biting forces (Eves et al., 1988; Hylander & Johnson, 1989; Kemsley et al., 2003). We can hypothesize therefore that some relationship also exists between sEMG and puncture test data, since the latter involves measurement of a force exerted upon compression. However, this represents something of a challenge, given the comparatively narrow range of textural qualities encountered within a single fruit variety.

For the data set taken as a whole, we found that there is indeed a highly statistically significant relationship between the integrated sEMG intensity and the puncture test data. Furthermore, an exploration of this relationship as a function of frequency showed that the greatest correlation is obtained when the sEMG signal is integrated across higher frequencies only, and for the present dataset, specifically using parts of the spectral region greater than 15Hz. For example, figure 15(a) shows the integrated sEMG signal across the region 15 - 100Hz obtained from each apple (calculated from the standardized, co-added data) versus the puncture test data, for the entire collection of 260 apples. The  $R^2$  value of 0.12 indicates that ~12% of the variation in the puncture test data can be explained by the sEMG data. In contrast, the frequency range below ~15Hz is the least well correlated with the puncture test data, with an  $R^2$  of just 0.05 in comparison. The low-frequency end of the sEMG spectrum reflects gross muscle movements, whereas higher frequencies represent activation of fast and slow muscle groups (Wakeling, 2004). We surmise that it is the latter portion of the spectrum that contains information most analogous to the puncture test measurements.

This relationship was explored in more detail on a per-subject basis. It is found that there is variation in the extent to which each individual's sEMG data correlates with the penetrometer values (table 1). However, all except one of the volunteers showed a positive relationship with the penetrometer data, and for seven of these, the relationship was significant ( $p < 0.05$ ) and in some cases highly so: see for example figure 15(b).

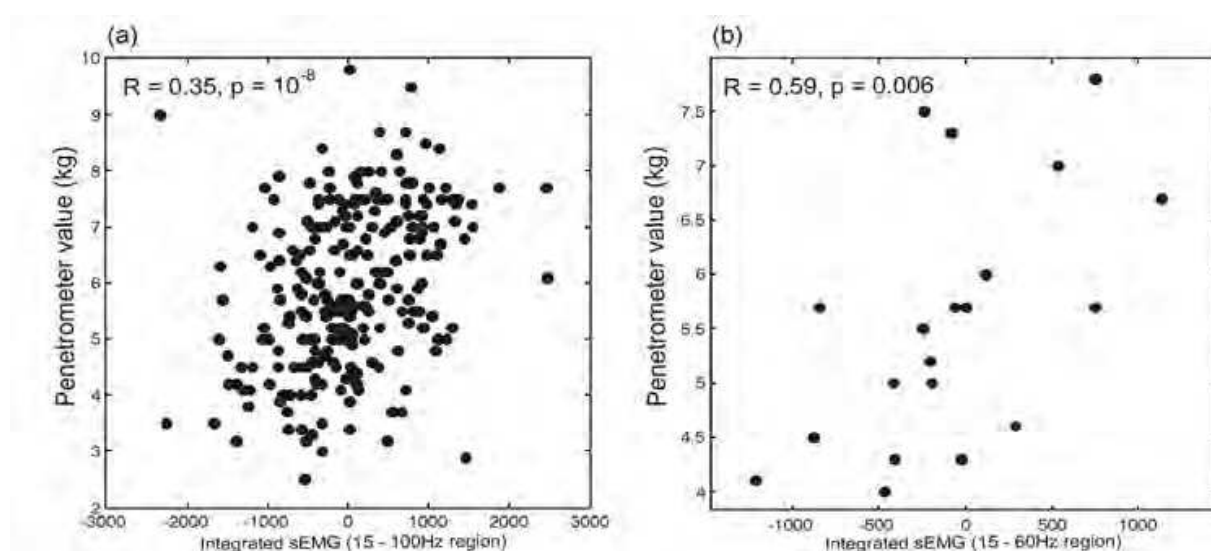


Fig. 15. Examples of the relationship between integrated sEMG data (standardized across batches of data from each volunteer and session) and the mean penetrometer values. Both the sEMG and penetrometer data were averaged to give per apple values. In (a), the relationship for the whole data set is shown (260 apples), and the sEMG integration was carried out across the 15 – 100Hz region. In (b), data from one volunteer only are used (volunteer code 59; 20 apples). Here, the sEMG integration was carried out across the 15 – 60Hz region only.

Regression of penetrometer values onto sEMG			
Volunteer code	Pearson's correlation coefficient, R	R-squared	p-value
50	0.14	0.02	0.56
51	0.63	0.39	0.00
52	0.13	0.02	0.59
53	0.41	0.17	0.07
54	0.50	0.25	0.02
55	0.64	0.41	0.00
56	-0.04	0.00	0.87
57	0.57	0.32	0.01
58	0.38	0.15	0.10
59	0.59	0.35	0.01
60	0.10	0.01	0.68
61	0.45	0.20	0.05
62	0.50	0.25	0.03

Table 1. Details of individual regressions of per apple penetrometer values onto each volunteer’s sEMG data, integrated across the 15 – 60Hz region. Significant ( $p < 0.05$ ) positive relationships were found for seven of the volunteers, indicated by grey shading of the table rows.

### 3.5 Modelling sensory properties

The relationships between sEMG and the sensory evaluations were also explored, in particular for the properties “hardness” and “mealiness”. For these two terms, we find that there are respectively clear positive and negative relationships with the sEMG data. Figure 16 shows the plots of the sensory scores for each term versus the sEMG data (figures 16(a) and (b)), and additionally the sensory scores versus the penetrometer data (figures 16 (c) and (d)). This illustrates well the similarity between sEMG and puncture tests in terms of their ability to model the sensory properties; compare the corresponding upper and lower figures in each case. Positive relationships also exist with juiciness and skin toughness (not shown), but these are much weaker, and for skin toughness, barely statistically significant. Again, a pattern of frequency dependence was found in the sEMG data: for all sensory terms, it was advantageous to integrate parts of the spectra above around 15Hz, with frequencies below this having least correlation with the sensory data. This is an important finding: it indicates that the least useful part of the sEMG power spectrum is the low-frequency region; yet it is this region that relates to the type of information that is conventionally extracted from time-domain sEMG.

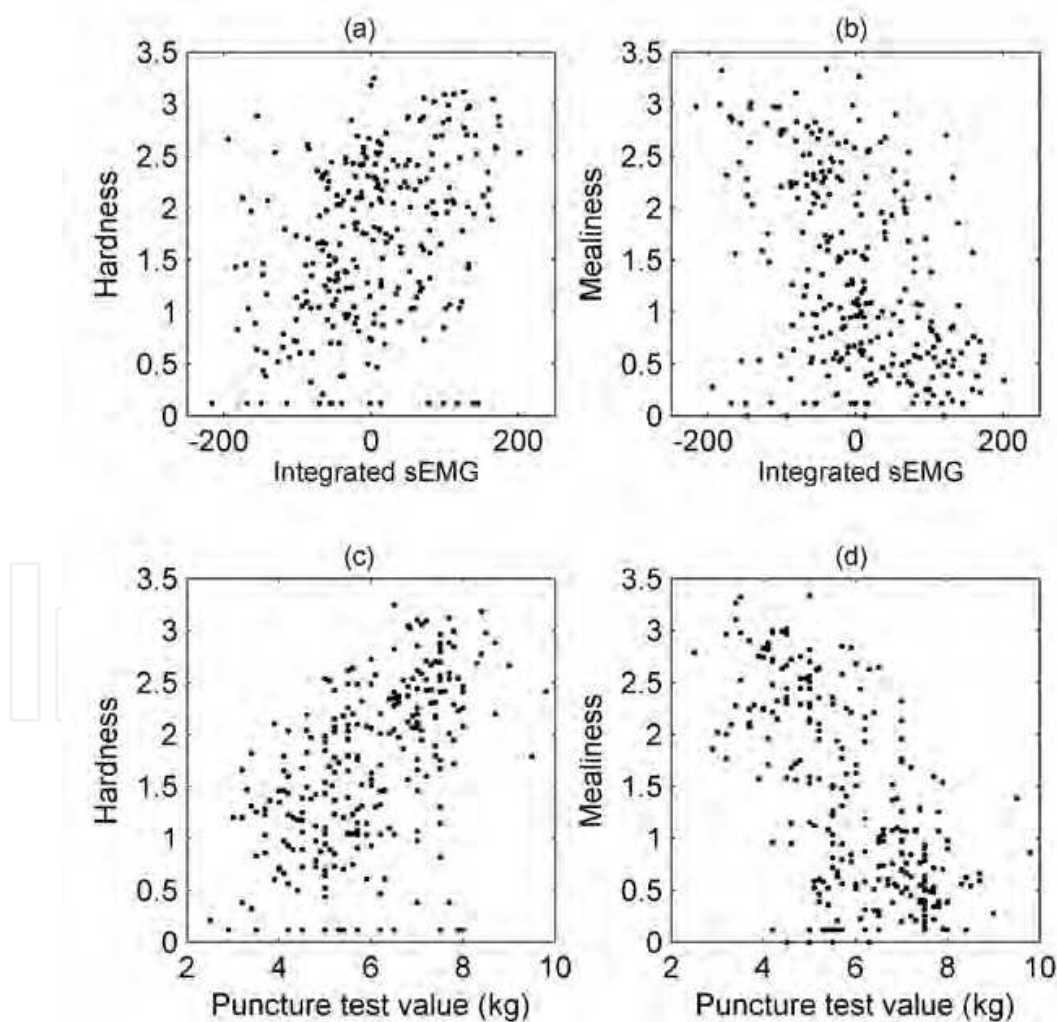


Fig. 16. Sensory hardness and mealiness versus (a) and (b) integrated sEMG signal, and (c) and (d) puncture test data. Note the qualitative similarity of plots (a) and (c), and (b) and (d).

### 3.6 Modelling sensory mealiness

We now focus particularly on sensory mealiness as the dependent variable of interest, since it is this property that is most challenging to measure by objective means. Sensory mealiness scores were regressed respectively onto the puncture test data, onto the sEMG data, and onto both using bivariate linear regression. All analyses were conducted on a per subject basis, and the sEMG data comprised integrated power spectra in the region 15 – 60Hz. The R<sup>2</sup> values are given in table 2, along with an indication of significance. There is significant (p<0.05) correlation of sensory mealiness with the puncture test for all subjects except one. sEMG was also found to be an effective predictor for eight out of the thirteen subjects, although the relationships (and significance levels) were generally somewhat weaker. However, this represents a substantial improvement compared with a previously reported analysis of the sEMG data (Ioannides et al., 2007) which used parameters extracted from the sEMG time domain signal, and found significant relationships for only four out of the thirteen subjects.

Volunteer	Regression of sensory mealiness onto puncture test data		Regression of sensory mealiness onto sEMG		Regression of sensory mealiness onto puncture test and sEMG data	
	Rsquared	p-value	Rsquared	p-value	Rsquared	p-value
50	0.67	0.00	0.10	0.18	0.71	0.00
51	0.61	0.00	0.49	<0.01	0.69	0.00
52	0.20	0.05	0.15	0.09	0.31	0.04
53	0.52	0.00	0.07	0.26	0.52	0.00
54	0.19	0.05	0.07	0.26	0.19	0.16
55	0.39	0.00	0.48	<0.01	0.54	0.00
56	0.52	0.00	0.00	0.92	0.52	0.00
57	0.54	0.00	0.23	0.03	0.54	0.00
58	0.43	0.00	0.27	0.02	0.51	0.00
59	0.65	0.00	0.53	<0.01	0.75	0.00
60	0.02	0.51	0.21	0.04	0.23	0.11
61	0.48	0.00	0.21	0.04	0.51	0.00
62	0.49	0.00	0.25	0.03	0.52	0.00

Table 2. Results of univariate regressions of sensory mealiness onto respectively puncture test and sEMG data, and bivariate regression onto both.



Examining now the results from the bivariate models, we see that there is better modelling of sensory mealiness in comparison with using either of the variates alone. Indeed, for the majority of subjects, the explained variance ( $R^2$ ) is appreciably greater. For 10 out of the 13 subjects, ~50% of the variance in their sensory mealiness scores can be explained by the combination of sEMG and puncture test data. Furthermore, the standard deviation of the regression residuals is typically comparable in magnitude to the repeatability of the mealiness evaluations, obtained by examining the replicate blind evaluations made on the same apple halves at each session (see Ioannides et al., 2007). We conclude that the sensory mealiness has been modelled as well as could be expected, given the intrinsic error associated with the measurements involved.

#### 4. Conclusions

The greatest obstacle preventing the use of sEMG as a routine measurement tool is that it is inherently a noisy technique. sEMG data suffers from a large amount of random noise, arising from the fact that the electrical signals generated by muscle activation are very small. This means that in practice, the SNR needs to be improved through signal-averaging by various means (for instance, co-addition of signals across replicate samples). A further considerable difficulty is that sEMG data are also affected by multiple sources of systematic noise. It is established that volunteer and recording session are major sources of unwanted variance, as demonstrated in the first sections of this chapter. We also show that an additional potential source of systematic variance is psychological in origin: changes in mastication behaviour arise from differences in the instructions given to the subject. This is strong evidence for an effect that has been speculated upon in the literature, namely that sEMG measurements are systematically affected by the nature of the sensory evaluation that the subjects are asked to make. This has clear implications for researchers engaged in sensory work.

In our analyses, we have surmounted the problems of systematic noise by using standardization of the sEMG spectra. This implicitly assumes that across each batch of data being standardized, subjects are experiencing broadly the same range of sample properties. A potential improvement to this procedure might be to ask subjects to consume standard reference materials, to establish fixed sEMG scale limits for each data subset. However, provided each session includes a sufficiently representative range of the samples under study, we have found that the within-session standardization approach is effective in allowing batches of data from different volunteers and sessions to be concatenated, increasing the power of statistical tests and the ability to explore underlying sources of information in the data.

Once the sEMG data have been appropriately treated, we find that they contain information that can be related directly to other physical properties of the foodstuffs, both mechanical and sensory. In studies of two different foodstuffs, edible gels and apples, positive and significant correlations were obtained between sEMG power spectra and mechanical measurements relating to texture. Further detailed analysis of the sEMG data in the apple study uncovered a frequency effect in the relationship between sEMG power spectra and other measurements (sensory evaluation, puncture tests) relating to texture; specifically, higher frequencies (>15Hz) proved the most useful. The work on prescribed chewing had

indicated that these higher frequencies were also the least affected by major changes in gross chewing movements. In previous work on the apple data, we used parameters extracted from the time-domain sEMG signal, analogous to the low-frequency end of the power spectrum, and the number of subjects for which significant relationships were found was lower. We conclude that a fruitful approach to sEMG analysis is to use frequency-domain signals, standardized for session and subject, signal-averaged across each sample and integrated across frequency ranges above 15Hz.

## 5. Acknowledgement

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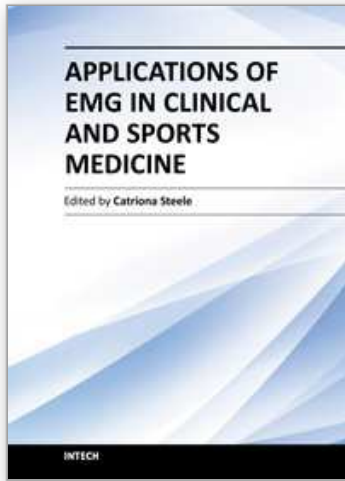
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