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A quantitative information measure applied to texture perception attributes during mastication

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Abstract

We have calculated an entropy or information measure of previously reported experimentally determined temporal dominance of sensations (TDS) data of texture attributes for two sets of emulsion filled gels throughout the mastication cycle. The samples were emulsion filled gels and two-layered emulsion filled gels. We find that the entropy measure follows an average curve, which is different for each set. The specifics of the entropy curve may serve as a fingerprint for the perception of a specific food sample.

KEYWORDS

entropy, food, information, sensory, TDS, texture

1 | INTRODUCTION

The perception of texture while we consume food results, in part, by the ability of our brain to combine electrical signals that arrive from our five sense organs via the nerves (Rolls, 2005; Rolls et al., 2003; Verhagen & Engelen, 2006). The combination of signals is exemplified by the existence of texture-taste interactions (Burns & Noble, 1985) and texture-aroma interactions (Bult et al., 2007; Saint-Eve et al., 2004). On the other hand, this perception is influenced by previous experiences (Mojet & Köster, 2005), mood (Gibson, 2006), eating behavior (Devezeaux de Lavergne, Derks, et al., 2015), social setting (Cardello et al., 2000; King et al., 2004), and location (Edwards et al., 2003; Stroebele & De Castro, 2004). The complexity that is involved in the integration of all of these aspects makes understanding texture perception resulting from food consumption a challenging task.

During food consumption, an important datum is the time of swallowing. Two material properties that have been pointed out as worthwhile to monitor after this juncture, are the degree of structure and the lubrication of the food material (Hutchings & Lillford, 1988). Because various food materials exhibit a various degrees of structure and lubrication upon swallowing (Hutchings & Lillford, 1988), it has not yet been possible to develop one quantitative mechanistic model during mastication until the moment of swallowing.

Besides the specific time of swallowing, it is important to quantify texture perception over the entire mastication time. During the past decades several new developments have come to the fore. One consisted of introducing a division between visual assessment, first bite, early and late mastication, swallowing and residual properties (Brandt et al., 1963). In this method (texture profile), each panel member needs to integrate the perception of each texture attribute over time to a single intensity value. A further development consisted of quantifying the temporal response of one specific texture related attribute (Larson-Powers & Pangborn, 1978). This is referred to as time intensity measurements. If one is interested in more than one attribute, the usual approach has been to repeat measuring time intensity profiles for each attribute (Guinard et al., 2002). Lately, temporal dominance of sensations (TDS) has been applied, a method in which, at each moment in time, the most dominant attribute is chosen (Pineau et al., 2009).

The latter method yields the frequencies of the most dominant attributes selected by the panel as a function of time. The time is usually normalized by the time duration between food intake to swallowing. For one type of food, depicting a variety of attributes, TDS yields a spectrum of attribute frequencies as a function of time (Di Monaco et al., 2014; Pineau et al., 2009).

There are two levels regarding the attribute selection of the most dominant attribute: one pertains to the individual panelists and the other to the panel. There is uncertainty in what an individual panelist selects as his or her most dominant attribute from a number of predefined attributes. This uncertainty also determines the distribution of the selected attributes at the level of the panel at a specific point in time. If there is agreement among panelists regarding the dominant attribute, the uncertainty is low or absent. With increasing disagreement, uncertainty regarding the selected dominant attribute also increases. An established measure for uncertainty is information (Rothstein, 1951; Shannon, 1948; Szilard, 1929). In the current context, uncertainty is a panel property that purportedly correlates with concepts like diversity of opinion, lack of consensus or disagreement.

The terms uncertainty and entropy can be related to one another as follows. According to Rothstein (1951), in physics one is interested in information obtained from a system by a measurement on the system. The amount of information obtained from a measurement equals the difference between the final information, I_f, and initial information, I_i, on the system. If the information (about the system) increases, the uncertainty (on the system) decreases. So, information on a system equals minus the entropy of that system. Or, as Rothstein put it: "… information obtained from a measurement equals the difference between initial and final entropies of that system." In short: $I_f - I_i = -(S_f - S_i)$ with S_f and S_i the final and initial entropy. As for having another perspective on entropy we can refer to (Brillouin, 1956) "… The entropy is usually described as measuring the amount of disorder in a physical system. A more precise statement is that entropy measures the lack of organization about the actual structure of the system."

In sensory science, the concept of information has been used, for example, in experiments on absolute judgment (Garner & Hake, 1951; Miller, 1953, 1956), and on reaction times (Hick, 1952). It was also used for quantifying the maximum capacity of a person to perceive something and to process the information (Attneave, 1954; Miller, 1956; Munsinger & Kessen, 1964). A very recent example of the use of the concept of information can be found in the field of consciousness and awareness (Guevara Erra et al., 2016), who identified "features of brain organization that are optimal for sensory perception." They suggested that "consciousness could be the result of an optimization of information processing."

Given the possible importance of the concept of information to sensory science, and its relation to uncertainty, we set out to quantify the latter, for a specific set of previously reported TDS data (Devezeaux de Lavergne et al., 2016; Devezeaux de Lavergne, van Delft, et al., 2015) by using established information theory.

2 | MATERIALS AND METHODS

2.1 | TDS data and preprocessing

In our analysis we use previously published data of TDS studies on various samples with texture attributes only. They have been described elsewhere in more detail, with regard to the experimental method and panel size, (Devezeaux de Lavergne et al., 2016; Devezeaux de Lavergne, van Delft, et al., 2015). Two sets of samples were studied. The first were eight emulsion-filled gels with different mechanical properties (Devezeaux de Lavergne, van Delft, et al., 2015). The gels varied with regard to the fracture stress (low and high), the fracture strain (low and high) and the emulsifier used (WPI or Tween 20) making emulsion oil droplet bound and unbound to the gel matrix. The second set were 10 emulsion-filled gels bearing mechanical contrast (Devezeaux de Lavergne et al., 2016). They consisted of two layers with different mechanical properties (low or high gelatin, LG or HG, respectively, or low or high agar concentration, LA or HA, respectively).

Panels determined the sensory perception for a variety of attributes. Participants were selected based on their "discriminatory abilities" for the different textures. They had extensive experience with sensory experiments with semi-solid model foods and Qualitative Descriptive Analysis (QDA) (Devezeaux de Lavergne et al., 2016, Devezeaux de Lavergne, van Delft, et al., 2015).

During the TDS experiment a number of panelists, n_p, were asked to select the most dominant attribute during mastication of a sample from a list of pre-defined number of attributes, N_a. The predominant of an attribute was defined as "the attribute that attracts the most attention at a given point in time." The experiment was set up in such a way that only one dominant attribute can be selected by a panelist at any given time during mastication. The selected attribute was considered dominant until the next attribute was selected. The attribute sequence obtained is then registered as a binary response: data are coded as "0" if the attribute, a_i, is not dominant at a certain time and "1" if it is dominant. For each measurement and each panelist, the time starts when they place the sample in their mouth (defined as $t = 0$) and stops when they swallow the sample (defined as $t = 100$). Each panelist repeats their selection of the predominant attribute for each type of sample as a function of time, with a number of repetitions, n_r. For each measurement, a panelist may need a different mastication time. We normalize the time during mastication by the total mastication time of each panelist in order to obtain normalized time from 0 to 100. The samples were presented to the panel in a randomized design. We define the probability of attribute selection, a_i, by the panel at time t, by, $p(a_i|t)$. Setting the total number of times that an attribute is chosen by the panel at a normalized time t as n_a, we have $p(a_i|t) = n_a/(n_r n_p)$. Analyses were conducted in R 3.2.5 (R Core Team, 2018). The statistical analyses have been displayed in the Supplementary Material, from Figures S1 to S29. The TDS curves for all samples can be found Figures S1 and S15 in the Supplementary Materials.

2.2 | Information theory

As we have outlined in the Section 1, information equals minus entropy in a formal sense. Applying the expression for the total entropy $H(t)$ to our case in the panels selection of an attribute a_i at a given time t, which is defined terms of the attribute selection probability $p(a_i|t)$, we have:

$$H(t) = -K\sum p(a_i|t)\log_2 p(a_i|t), \tag{1}$$

Here, the normalization factor $=1/\log_2 N_a$, with $\log_2$ denoting the logarithm with base 2, and where Σ denotes the summation over all attributes a_i in the set. The total information is $I(t)$.

Equation (1) states that when the probability that an attribute is selected at a certain time is equal to 1, the uncertainty (entropy) is zero. In this case, there is only one attribute perceived as predominant for the whole panel, the panelists fully agree with each other and there is no uncertainty about the attribute; in other words, no (new) information is gained from the selection of the attribute. However, when the probability for the selection of all attributes is $1/N_a$, the uncertainty with respect to the selection of an attribute becomes equal to unity. Then, all attributes have an equal probability to be selected by the panel. Then the uncertainty, that is, the level of disagreement is at a maximum. Information is to be gained from the selection of an attribute.

It takes a certain time—lag time—for a panelist to select a dominant attribute (see Figures S2 and S16; Supplementary Materials). The lag time is different among panelists. As they continue to masticate, panelists start to perceive the attributes and select their first predominant one. Because of the lag time, we have to introduce a so-called estimator. Our choice, the Chao-Shen estimator, accounts for the fewer selected attributes in the beginning of mastication and purportedly ensures that the uncertainty is not over- or under-estimated (Chao & Shen, 2003; Hausser & Strimmer, 2008). It is defined by

$$\widehat{H(t)} = -K\sum \frac{p\widehat{(a_i|t)}\log_2 p\widehat{(a_i|t)}}{\left(1-\left(1-p\widehat{(a_i|t)}\right)^{n_a}\right)} \tag{2}$$

where $p\widehat{(a_i|t)} = \left(1-\frac{m}{n_a}\right)p(a_i|t)$, with m the number of attributes that is selected only once out of $n_r n_p$ measurements, and n_a is the total number of selected attributes at time t. When none of the panelists haven selected an attribute, the entropy is set to zero. The entropy is also zero when all panelists, have selected the same attribute as the predominant one. Both cases occur in the beginning of mastication, when not all panelists have started recording their predominant attribute. We treat points in time for which $\widehat{H(t)} = 0$ as missing values (see also Figures S3 and S17; Supplementary Materials).

2.3 | Model

It turned out that the dependence of the entropy as function of normalized time could not be fitted to a low order polynomial. Instead, we used Generalized Additive Mixed Models (GAMM) to fit statistical models to the data. The GAMM models were implemented using the mgcv R package by Simon Wood (Wood, 2017) that also allows one the time series to deal with the auto-correlation.

The following methodology was adopted: in order to capture the GAMM curves in a qualitative way, all curves were compared to a reference curve, which is here defined as the average entropy of all samples versus time. The data were fitted with an upper limit of $k = 25$ knots. Cross-validation selected the optimum number of knots to prevent over-fitting (Supplementary Materials; Figures S4–S13, S18–S27). The predicted values of the reference curve were then subtracted from the entropy data, and the model without auto-correlation was reevaluated based on the transformed, new, data set. The residual curvature, relative to the selected reference curve, was then tested for residual nonlinearity and was visualized (Supplementary Materials; Figures S14 and S29).

3 | RESULTS AND DISCUSSION

3.1 | Information and TDS data

Figure 1 (Right) shows the entropy as a function of normalized mastication time for one sample (TDS frequency curve of the same sample in Figure 1 (Left), Supplementary Materials; Figure S1 for TDS data of other samples and Figure S3 for entropy over time for other samples displays). In the beginning, the entropy (uncertainty) is low: the panel is just starting to perceive the sample and they are selecting their first predominant attribute. During the first few designated points in time the entropy actually equals zero (indicated in red in Figure 1b). This is because none of the panelists have selected an attribute, or the few panelists that have selected an attribute have selected the exact same one. No proper selection can be drawn from this so these points are treated as missing values during the fitting of the model. As mastication continues, the sample is broken down and mixed with saliva. This alters the structure of the sample and thus the perceived texture. Upon further mastication, the food is broken down even further, and a swallowable bolus is formed. The entropy related to the predominantly perceived attribute decreases and reaches a maximum in the middle of the mastication process. The panel is no longer in agreement about the predominant feature at that time. A variety of attributes may get selected. The entropy (uncertainty) approaches its maximum value. The panel subsequently reaches more agreement about the predominant attribute as can be seen from the subsequent decrease of entropy. At the moment of swallowing the entropy is

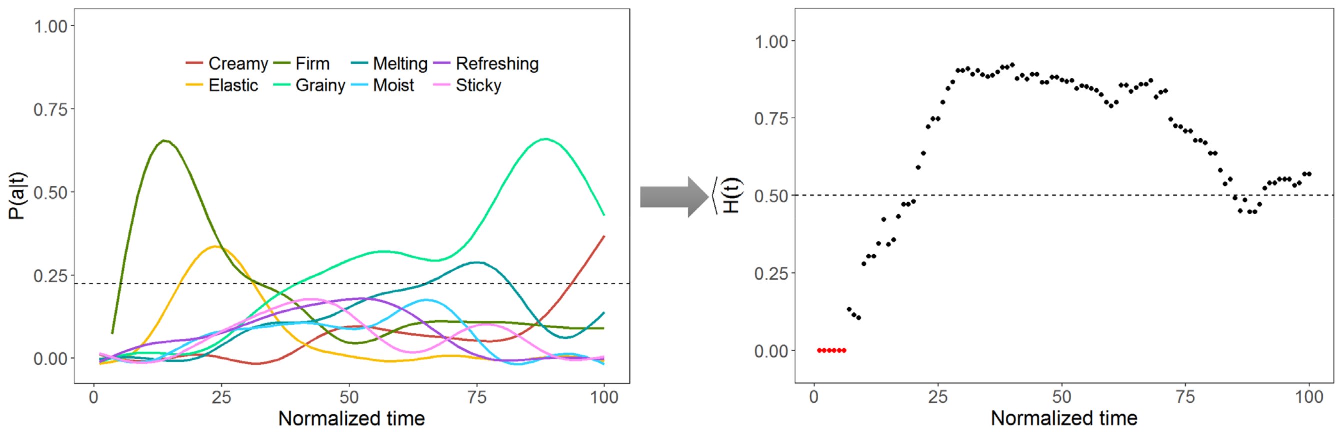

FIGURE 1 (Left) Temporal dominance of sensations plot of one sample of emulsion filled gels (the sample had high engineered fracture stress (σ) and low engineered fracture strain (ϵ) and WPI as an emulsifier) (the reader is referred to the supplementary materials; Figure S1 for the plots for the other samples in set 1). (Right) Temporal entropy for the same sample. Red points have an entropy of 0 and are treated as missing values for the fit (the reader is referred to the supplementary materials; Figure S3 for the plots for the other samples in set 1). Time is normalized as a % of total mastication time per measurement ($n = 10$, triplicate). TDS data from Devezeaux de Lavergne, van Delft, et al. (2015).

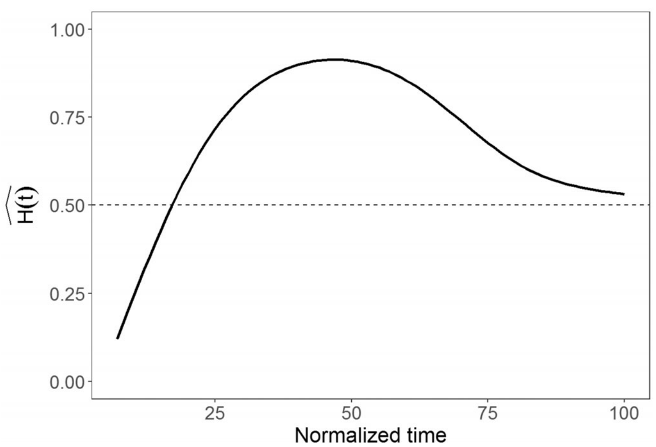

FIGURE 2 Temporal entropy GAMM fit for one sample, same sample as Figure 1 (the sample had high engineered fracture stress (σ) and low engineered fracture strain (ϵ) and WPI as an emulsifier). Missing values are removed. Time is normalized as a % of total mastication time per measurement ($n = 10$, triplicate). TDS data from Devezeaux de Lavergne, van Delft, et al. (2015).

about 0.5. We note that this implies that, more than one attribute is perceived as predominant. This in turn implies that there is no single attribute responsible for triggering the act of swallowing.

Figure 2 displays the GAMM fit to the temporal entropy of one sample. The optimum number of knots to fit the data was six. The best fit was obtained for a model that includes a possible autocorrelation with respect to the (normalized) time. The autocorrelation implies that the entropy at a point in time is influenced by the entropy at a previous time which seems to be a sensible assumption.

Figure 3 (Left) displays the entropy curves for a variety of samples with different mechanical properties. The samples varied with respect to fracture stress (low and high), fracture strain (low and high), and the emulsifier used (WPI or Tween 20). Even though the mechanical properties of the samples were disparate, we discern that the (normalized) entropy curves follow the same pattern. At the start of mastication, the entropy (uncertainty) is low, so there is agreement concerning the predominant attribute. In the middle of mastication, the entropy reaches a maximum, there is no agreement about the predominant attribute and a variety of attributes are being selected by the panel. Toward the end of mastication, the panel reaches more agreement concerning which attribute is predominant and the entropy (uncertainty) decreases again, but not to zero. Again, apparently more than one attribute is being perceived at the start of the swallowing process and there is no single attribute responsible for triggering the swallowing action. Figure 3 (Right) shows the mean entropy as a function of time for the set of samples. In general, all curves follow a master curve, if we take into account the 95% confidence level indicated in the figure. Samples $H\sigma L\epsilon T$ and $L\sigma L\epsilon T$ end up higher (with 95% confidence), while samples $H\sigma L\epsilon W$ and $L\sigma H\epsilon W$ have a lower entropy upon swallowing (with 95% confidence). Samples $L\sigma L\epsilon W$ and $L\sigma H\epsilon T$ have a higher entropy at the beginning of mastication (See also Figure S14 in Supplementary Material). Both $H\sigma L\epsilon T$ and $L\sigma L\epsilon T$ have a low fracture strain and their oil droplets were emulsified with Tween 20. This means that they are brittle gels and their oil droplets are not bound to the matrix. Because of the brittleness, there is a high probability that they are perceived as grainy rather than creamy. The brittleness apparently leads to a higher uncertainty in the selection of the attribute.

Figure 4 (Left) shows the entropy curves for emulsion filled gels that exhibited a mechanical contrast. They consisted of two layers with different mechanical properties (low or high gelatin or agar concentration). The entropy follows the same general curve as that of the samples in Figure 3. One sample (HA + HA) contains two of the same layers with a high agar concentration and it shows a significantly lower entropy than the others. Gels with a high agar concentration are very brittle which renders the sample firm at first and then grainy later on. During mastication, there is therefore a high probability that

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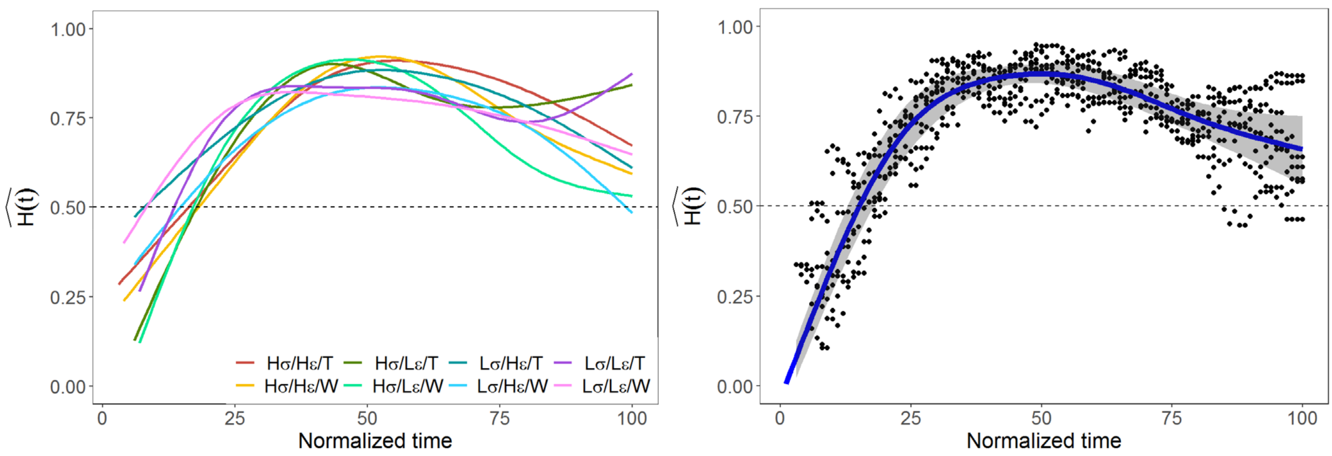

FIGURE 3 (Left) Temporal entropy GAMM fit curves of emulsion-filled gels (with low [L] or high [H] engineered fracture stress [σ] and strain [ϵ] and WPI [W] or Tween 20 [T] as an emulsifier). (Right) Temporal entropy for all samples. Points with an entropy of 0 are treated as missing values. Blue line indicates the GAMM fit to the mean entropy over time. The shaded area is the 95% confidence interval for the fit. Time was normalized as a % of total mastication time per measurement ($n = 10$, triplicate). TDS data from Devezeaux de Lavergne, van Delft, et al. (2015).

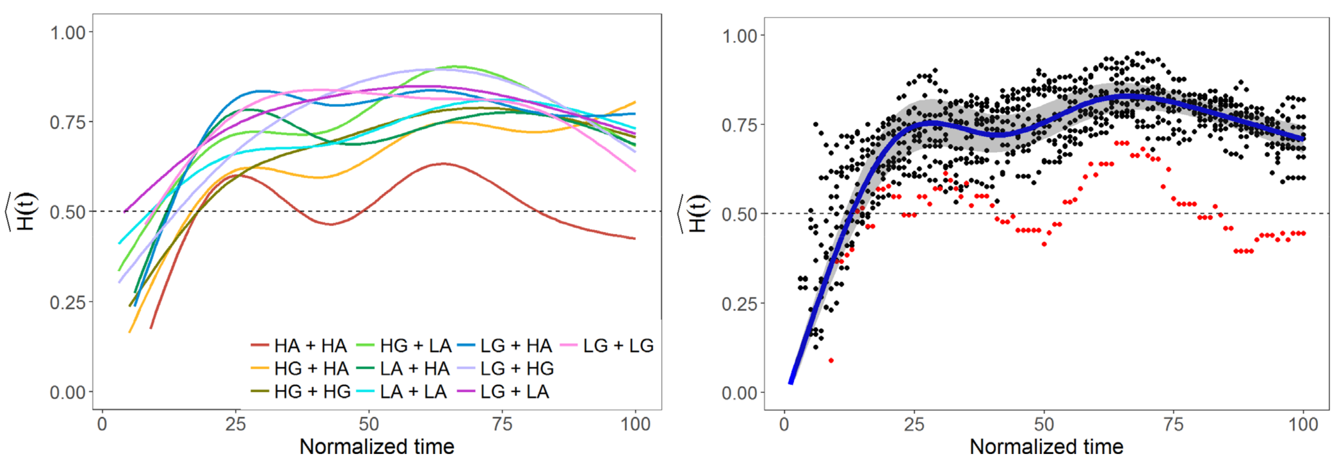

FIGURE 4 (Left) Temporal entropy GAMM fit curves of emulsion filled layered gels with mechanical contrast (low [L] or high [H] gelatin [G] or agar [A] concentration). (Right) Temporal entropy for all samples. Points with an entropy of 0 are treated as missing values. Sample HA + HA (indicated in red) is considered an outlier and is not taken into account for the mean fit. Blue line indicates the GAMM fit to the mean entropy over time. The shaded area is the 95% confidence interval for the fit. Time was normalized as a % of total mastication time per measurement ($n = 10$, triplicate). TDS data from Devezeaux de Lavergne et al. (2016).

it is being perceived as grainy, which reduces the uncertainty about the perceived texture, which is a likely explanation for why the curve of HA + HA shifted to a lower value than for the other samples. The mean of entropy for this sample is indeed an outlier in a boxplot (see supplementary materials; Figure S28) and thus the sample can be considered an outlier for the mean entropy curve, with the likely explanation given above.

In this case the panel was more experienced with the TDS technique. Such panels tend to select their first attribute faster than panels with little experience (after 2.0 ± 1.3 s on average compared to 3.4 ± 2.3 s on average for the less experienced panel). In view of this, the uncertainty rises more steeply in the beginning and reaches a longer plateau in the middle, which can be seen in Figure 4. The longer plateau exhibits a fluctuation in entropy in the middle of the mastication process, which we attribute to the fact that the gels exhibit a mechanical contrast.

Figure 4 (Right) shows the mean entropy versus time for the set of samples. In general all curves follow a master curve except for sample HA + HA which is clearly outside the confidence interval and for which we have given an explanation above.

From the results discussed until now we conclude that the temporal entropy curves follow the same pattern, independently of sample categories or the panels. The entropy starts at a low level at the beginning of mastication and rises in the middle of mastication. Toward the point of swallowing the entropy of selection of the predominant attribute tends to decrease again except for the case of the two gels $H\sigma L\epsilon T$ and $L\sigma L\epsilon T$ in the first data set and for the two gels HG + HA and LG + HA in the second data set. We note that the entropy upon swallowing is still higher than 0.5, in line with the fact that there is no single predominant attribute that triggers swallowing. It is likely that a typical panelist unconsciously searches for a pattern related to a bolus that is safe to swallow and which does not exhibit an unexpected attribute.

We now discuss the choice of attributes during the TDS experiment. The texture attributes how we selected are generally based on the results from either a Quantitative Descriptive Analysis (QDA) experiment (Devezeaux de Lavergne, van Delft, et al., 2015) or from previous studies (Devezeaux de Lavergne et al., 2016). In the experiments discussed here, we have chosen chew-down attributes. The attributes to be scored in the TDS experiment are carefully selected to be applicable to the entire set of samples, and the panelists discuss the attributes before the TDS experiment. We have to realize that a panelist can only actively choose from a limited number of attributes, which, according to Pineau et al. (2012), amounts to about 10. If there are more attributes in the list, not all attributes are used by the panel. The number of attributes in the experiments discussed above was eight (samples in Figure 3) or nine (Figure 4).

Furthermore, the predominance of one attribute should not last too long. This is because if one attribute were to constantly overpower the others, the uncertainty would stay around 0.5 and the uncertainty with regard to the other attributes, although perceived, would not be accessible (Devezeaux de Lavergne, 2015). This is due to the set-up of TDS where the panelists keep the set of attributes in their mind and need to select the predominant attribute while consuming and masticating the sample. This may be the case in sample HA + HA (cf. Figure 4).

The amount of training of the panel may play a role also in the form of the curve; in particular their experience with sensory experiments and the TDS experimental set-up are important (Meyners, 2011). Interestingly, the panel that performed the experiment with the gels with contrasting layers was more experienced and selected their first dominant attributes earlier than the panelists scoring the gels in Figure 3.

We conclude that for two categories of samples most samples within each set follow a master curve. The detailed shape of the master curve depends on the specific category. The overall shape is one of a steep rise, a maximum, and a small decline before swallowing. The time dependence of the entropy may thus serve as a way to fingerprint perception properties of food categories as a quantitative indicator of the influence of expectation of attributes being present before consumption.

3.2 | Further remarks

We would like to mention several aspects of information theory in relation to perception that have not been sorted out in the literature and that may be relevant to our discussion above. First of all, during perception, there is a physical interaction between the stimulus and the perceiver, and they may influence each other (Nizami, 2011). By contrast, in the communication system that Shannon describes, the system is in no way altered by the stimulus. Luce (2003) indeed indicates that Shannon himself was skeptical about the use of information theory outside communication engineering. A second point to keep in mind is that people do not behave like static electronic devices; they do not possess a "fixed immutable information processing capacity" (Baddeley, 1994). Indeed, with practice, the reaction time to a stimulus levels off. Yet another issue is that messages in Shannon's theory of communication often contain redundancy. This helps with encoding and recovering the sent message, even in the presence of noise (Shannon, 1948). But, during perception redundancy does not always hold (Luce, 2003). A fourth important issue of contention could be that, in contrast to standard information theory, stimuli in psychological experiments have different levels of structural organization and should therefore not be treated as mutually independent statistical events (Aksentijevic & Gibson, 2012). Nevertheless, there are proponents of applying information theory to sensory science. For example, according to Norwich (2003), perception involves the selection of several choices, which purportedly renders information theory quite suitable to apply to problems of perception. Moreover, Laming (2001) puts forward that the usual information theory can still "provide a 'non-parametric' technique for the investigation of all kinds of systems without the need to understand the machinery, to model the brain without modelling the neural responses."

We note that our measure of entropy is calculated on the basis of averaging over the responses of all panel members and replications. In the current experimental set-up, the same experiment on each panel member has been performed only three or four times to check for intra person variability. Many more repetitions would not increase the accuracy of the data per panel member, for it would introduce learning and anticipation into the experiment.

In regards to the effect of learning/anticipation we note that the form of the temporal entropy may serve as a quantitative indicator of the influence of expectation on the attributes to be encountered. This idea could be tested by performing similar food sensory studies where information provided before consumption is varied while not all product details are known to the consumer. In a broader sense, the same idea could be tested on persons that are playing a game; the entropy as derived from the number of different decisions made during the game, may be inversely related to (some power of) the number of previous experiences with the game.

Despite the fact that the application of information theory to sensory science has not reached overall agreement, we think that the two average curves for TDS data for the two different sets of emulsions-filled gels provides useful information for the field of sensory science. In particular, it alludes to a way of categorizing foods and to better analyze TDS data. This may be as simple as the tendency to only swallow the bolus at the moment it is safe to swallow (as proposed by Hutchings and Lillford (1988)), and where the perception of the other attributes during chewing would then be a side effect. However, the perception of the other attributes during chewing may still be important. In this respect the work by Guevara Erra et al. (2016) on brain function is interesting; they observed a maximum in entropy during normal wakeful states. These authors expressed the hope that their findings could represent a "preliminary attempt at finding organising principles of brain function." In the same way, our results may be a starting point in identifying organizing principles during sensory perception.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ETHICS STATEMENT

The research is a theoretical exercise on already existing data obtained previously.

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