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High-bandwidth tribometry as a means of recording natural textures

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***Abstract*— The measurement of perceptually relevant information about textures has been approached through profilometry, vibrometry, and tribometry. Manfredi et al. [1] used a laser Doppler vibrometer to measure skin surface vibrations as a texture sample slides across a fingertip. In our work, we treat the Manfredi et al. measurements as a gold standard, and assess the performance of a simpler and more portable device: a high-bandwidth tribometer. The tribometer was used to measure shear and normal forces applied to each of six texture samples as a fingertip scanned across them. The collected data was used to build two classifiers: one based on features extracted from the spectra (which treats the data as stationary); and a second based on the first through fourth order statistics associated with a set of band-pass filters (which treats the data as non-stationary). The results indicate that tribometry, while not as effective as vibrometry, may nonetheless prove effective as a means of recording natural texture. Additionally, we find that the non-stationarity of skin vibrations may serve as means of texture classification. Ongoing work aims to couple tribometric recordings with texture rendering and playback via surface haptic devices, and to understand the perceptual significance of non-stationarity in vibrations.**

I. Introduction

In everyday life, humans encounter a great variety of textures. What are the factors that distinguish one texture from another? Psychophysical studies typically point to a modest number of perceptual dimensions, such as rough-smooth, hard-soft, and warm cool [2]–[6], while other studies have pointed to underlying physical factors such as shape features [7], friction and stiction [4], [8], and spatial wavelengths [9], [10]. Of particular note are the vibrations induced by a finger scanning across a surface, which have received considerable attention in recent years [1], [11], [12].

While there is little doubt that texture-induced vibrations carry perceptually relevant information, only a few attempts have been made to extract such information from measurements. One approach is to employ the power spectra of finger-skin vibrations. For example, by correlating psychophysical and skin vibration measurements, Bensmaia [13] found that most of the perceived dissimilarity among a group of fine textures could be accounted for by spectral dissimilarities. Similarly, using the apparatus shown in Fig. 1, Manfredi et al. [1] found that the spectral content of skin vibrations could be used to classify a set of 55 textures with up to 93 percent accuracy.

The use of spectra, however, is subject to stationarity, a characteristic that may be absent in many natural textures. By way of example, consider a fabric like burlap: spectral content arising from the individual fibers is not uniformly distributed across space, but is modulated according to the coarse texture of the weave. The spectrum of a signal associated with burlap would be expected to be cyclostationary, but not stationary. Non-stationary signals may be analyzed using any of a variety of space-frequency or time-frequency techniques such as wavelets or the short-time Fourier transform (STFT) in the form of a spectrogram [10]. A related approach involves passing the time domain vibration signal through a set of band pass filters, then computing statistics based on the time-varying output magnitudes of the filters. Research in image and sound textures has demonstrated the value of these filter statistics in the creation of realistic synthetic textures [14]–[17]. Additionally, one recent study in haptics [18] showed that natural textures cluster according to the statistical parameters extracted from STFTs of shear force data, suggesting that such parameters may play a role in tactile perception. With a number of well characterized surface friction modulation haptic devices [19] identification and extraction of perceptually important parameters is one of the leading research motivations for the work presented in this paper.

In this paper we explore two questions. First, we ask how effective both spectra and filter statistics are when used separately to classify a set of vibration data obtained by scanning a finger across natural textures. We hypothesize that filter statistics will hold unique information by which texture can be classified. Second, we ask how effective high-bandwidth lateral force measurement (i.e., tribometry) is as a source of this data. While our group [18] and others [8], [20],

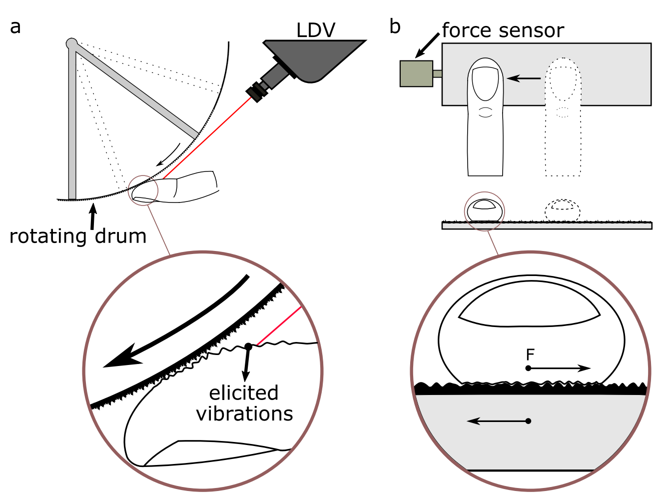

Fig. 1. (a) Side view of vibrometry device used by Manfredi et al. to capture texture information. (b) Top view of a tribometry device.

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[21] have used tribometric methods to record texture-induced vibrations, this work is the first to use these data in texture classification, especially via filter statistics. Additionally, by comparing to a well established vibrometric approach, we hope to establish that tribometry is a valid methodology, able to distinguish among natural textures and, potentially, to capture perceptually relevant information.

Our work is motivated by the desire to find a low-cost, robust, and rapid technique with which to capture perceptually relevant texture data. We wish to build a "texture camera". There exist a number of ways to collect skin vibration data (e.g. using a microphone to capture the sound elicited from finger during motion across a surface [22]), however, most methods limit the movement of the finger, reducing freedom in natural exploration. Laser-Doppler vibrometry may be employed for high precision acquisition of skin vibration presented in Fig. 1 but it typically requires a stationary finger, does not allow a direct measurement of data from the contact region between finger and surface, and can be expensive to integrate into a texture camera. Additionally, many surface haptic devices are based on friction modulation [23], [24], and would benefit by a direct and intuitive relation between lateral force and the rendered virtual texture. For these reasons, the tribometric approach presented in this paper offers an appealing alternative to vibrometry.

II. Methods

A. Apparatus

A custom-built, stationary-mount tribometer (Fig. 2) was used for data acquisition. One highly trained subject scanned his right index finger left to right across a texture sample mounted on the tribometer. Finger position was recorded by a high resolution (3.86 μm) encoder connected to a finger holder by a flexible metal wire. Each texture sample (on a carrier) was mounted magnetically to the tribometer platform. A piezo force sensor (Kistler 9203) was used to record lateral forces of finger texture interaction. This sensor was found to have a 3 dB bandwidth up to 1000Hz. Normal force was measured with two strain gauge sensors. The lateral force, position, and normal force sensors were sampled at 125kHz, and data were filtered according to their respective bandwidths.

B. Texture samples

To test the ability of the tribometer to capture perceptually relevant information, 6 natural textures, presented in Table I,

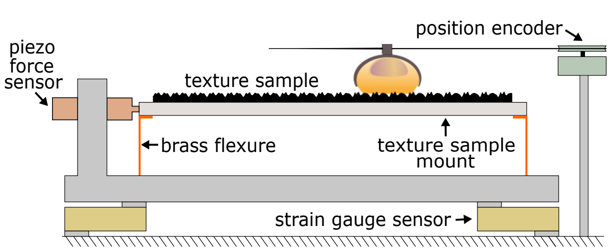

Fig. 2. Schematic representation of the tribometer.

1	Denim
2	Empire Velveteen
3	Faux Leather
4	Hucktowel
5	Microsuede
6	Swimwear

TABLE I
Scanned textures

were selected from the set used by Manfredi et al. Each texture was adhered to the surface of 25x80mm acrylic substrate using strong double sided masking tape. A thin steel sheet was adhered to the opposite side of the acrylic to enable magnetic mounting.

C. Experimental procedure

We recorded data at two scanning speeds common in patterns of free texture exploration: 80 and 120 mm/s [25]. We conducted 60 trials for each of the textures and each of the speeds resulting in 720 swipes.

Each scanning session lasted 30 s, during which the subject attempted to keep the velocity of each swipe constant and the normal force within $.5 \pm .1$N while scanning the texture left-to-right and right-to-left until the session time ended. Only the left-to-right data were retained. The subject used a metronome for pacing and had no knowledge of instantaneous scanning speed or normal force. The scanning velocity was allowed to deviate by 15% during phases where the subject attempted to keep a constant velocity. An algorithm was later applied to extract pieces of lateral force data 400 ms in length, that fell within the allowed range of deviation for normal force and scanning velocity, with the rest of swipes being discarded.

Every 5-10 sessions, or after a break, the subject wiped his finger with an alcohol pad in order to remove any moisture and dust collected on the finger. After being in use for some time, the microsuede and swimwear samples showed signs of deterioration and were replaced with new samples.

D. Data extraction and correction

Although the intent was to keep scanning speed constant during texture exploration, this could not be achieved perfectly. The higher speeds tended to occur in the middle of the movement range where our window function also peaked, over-emphasizing high-speed data. To correct for this, we stretched or compressed the time axis according to a local average velocity, effectively mapping the movement to one with the correct velocity. Shifting and sharpening of spectral peaks was readily observed post-correction.

E. Analysis

In order to evaluate the capability of the tribometer to capture information of value for texture discrimination, and to provide a basis for comparison with vibrometry, we examined two feature sets. The fist was based on spectral power, and the second was based on filter statistics. Vibrometry source data was provided by the Bensmaia Lab, and were the same data used in [1].

Spectral power information was analyzed by first dividing lateral force data by the corresponding normal force to obtain instantaneous friction coefficient data. This was then band-pass filtered by a second order Butterworth filter with cutoff frequencies of 51Hz and 600Hz, corresponding to the bandwidth of the vibrometry device. The filtered friction coefficient data was windowed with a Hanning window after which the power spectra were computed and normalized. For analysis of both vibrometry and tribometry data, we extracted a feature set consisting of power amplitudes at every integer frequency in the bandwidth range (550 features). A limitation to using most or all features was the spectral leakage due to windowing. Mutual information analysis showed that up to 10 neighboring integer frequencies are significantly correlated and therefore form a redundant feature set. With this in mind, we created 10 sets of 55 features each corresponding to unique set of frequencies spaced 10Hz apart. Classification results over the 10 sets were averaged, and reflect the overall quality of data sampled from the entire spectral bandwidth.

Because of a limited number of trials, further scaling of the over-complete feature set was necessary. A one-way ANOVA F-test rating computed by dividing between-class by within-class variance was used as a heuristic to extract the 5 most discriminative features from each of the 10 sets. The use of this metric reflects our intuition that features which are different across textures and highly repetitive across swipes are most likely to be utilized as perceptual cues. The F-test rating showed that most discriminant spectral features aligned with prominent spectral peaks of textures. In order to include a degree of freedom in the classification scheme that was not biased toward texture periodicity we added a feature that characterized the $1/f$ curve by which smooth and fine textures have previously been classified. We fit a function

$$\frac{\beta}{f^{\alpha}}$$

through normalized spectra and added α to the feature set increasing the number of features to 6. Parameter β was highly correlated to α and was therefore ignored as a feature.

The classifier algorithm uses Euclidean distance to measure the proximity of textures in the feature space. The basics of the technique are loosely adapted from the method used by Manfredi et al., with the steps outlined as follows:

1) Two sets, S_1 and S_2, are filled with N randomly selected spectra features for each texture and a given scan velocity, where $1 \leq N \leq 5$ and $1 \leq N \leq 30$ for vibrometry tribometry data respectively, and $S_1 \cap S_2 = \emptyset$.
2) The means of the spectral features from each of the two sets were computed and grouped by texture and velocity in two separate groups.
3) Each set of mean spectral features from one group corresponding to the same scan velocity was compared to those from the other. A cumulative error between the features of the two groups was computed by summing the absolute difference between the values corresponding to each of the features. A 6x6 matrix of error values (similar to a confusion matrix) was computed for each scanning speed. Every entry in the matrix corresponded to the distance between two textures within the feature set.
4) Classification accuracy based on similarity of mean spectral features was computed by summing the number of times a diagonal entry in a given matrix of error was the lowest value in its row. Perfect classification is observed when each of the diagonal entries is the smallest value in its row.
5) This process was completed multiple times for all scanning speeds, increasing N from 1 to 5/30 in order to evaluate the improvement in classification as function of the number of spectra used to compute the mean feature set. Because 8 subjects were involved in experimentation using the vibrometer, their classification results were averaged.

A separate feature set consisting of filter statistics was built as illustrated in Fig. 3. The basic idea here is to capture the non-stationarity of the underlying frequency content, as discussed in the introduction. To accomplish this, band-pass filters were first used to extract the signal in a set of frequency bands. An envelope was found for each filtered signal, after which we computed the mean value of the envelope (representing average strength of that band), its variance (representing variability of that band), it's skewness (representing envelope symmetry about the mean) and its kurtosis (representing the peakiness of the envelope). Note that envelopes contain rich information which can be further analyzed with auto/cross-correlations and envelope spectra, but here we sought only to understand whether it would be valuable to capture any degree of non-stationarity at all. We first apply a set of second order zero-lag filters to extract signal components of given band-pass frequencies. We then apply a Hilbert transform to compute the magnitude of band signal and low-pass filter it at the lower bound frequency of the underlying bandpass. The resulting magnitude of the signal constitutes its envelope from which statistical parameters are extracted.

One question is how to select the band-pass filters. Ideally, these filters would mimic the perceptual process, each one covering a band of indiscriminable frequencies. Although frequency JNDs are yet to be determined for a sufficiently wide range, research conducted on electrostatic devices has shown that values drop from 25% to 10% in the 80-400Hz range, with the steepest negative slope centered at 250Hz, before and after which a somewhat constant JND threshold value is observed. [24]. We therefore created a set of 16 bands which assume a 23% JND in 51-250Hz and and 10% in the 250-600Hz ranges. Using a similar F-test technique as before to separately extract 5 most salient features from envelope mean, variance, skewness and kurtosis, a set of classifiers was built based on these statistics alone. For computing 2nd-4th order statistical parameters the envelopes were scaled to range from -1 to 1 in order to remove any

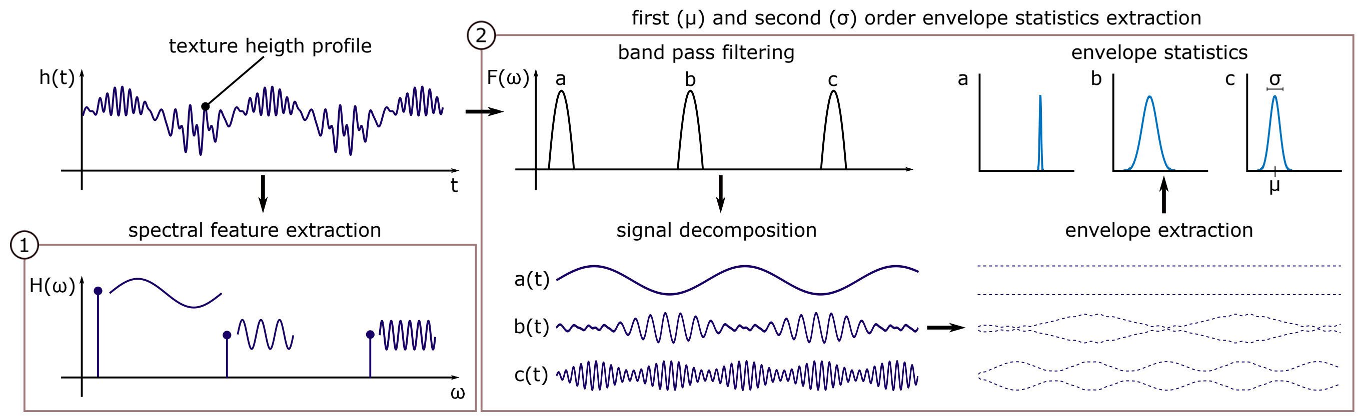

Fig. 3. Feature extraction as presented in this paper for a sample signal. Box 1 illustrates the computation of spectral features. In this illustration, only three frequencies have finite amplitude treated as a feature, but in practice we collected 550/600 amplitudes to generate the spectral feature set. Box 2 illustrates the computation of first and second order filter statistics. Although only three bands are shown, in practice we used 16.

correlation to the mean.

As described above, the tribometry data were limited to the bandwidth of the vibrometry to ensure a fair comparison. However, the tribometer with which data were captured is a high bandwidth device, prompting additional classifiers to be built to reflect information contained in a wider spectral range. Specifically, we wanted to see how much salient information is contained in the low frequency domain (1-50Hz) and at DC, which is inaccessible by vibrometry. An additional spectral classifier was built using tribometry data over the full 1-600Hz range, and a separate F-test analysis was performed on DC friction (although this was not incorporated into a classifier because it would have been difficult to compare to vibrometry).

III. Results

Classification accuracy as a function of the number of samples averaged is illustrated in Fig. 4 for both tribometry and vibrometry. At the lower speed of 80mm/s, vibrometry significantly outperformed tribometry when spectral features from the same frequency range were used; at 120mm/s the results were much more comparable. There are a number of possible explanations, one of which is the consistency of the vibrometry data due to the controlled conditions under which it was acquired. As explained in [1], the finger was adhered to a post, establishing a uniform normal force, and the textures were scanned across the finger at a steady rate. These measures would maintain the stationarity of the data to the extent possible.

The standard deviations shown in Fig. 4 illustrate the consistency of collected data. Thus, while classification based on 80mm/s tribometry data is close to 90% when spectral features from 30 samples are used, the relatively high standard deviation makes it apparent that some combinations of 30 samples are very different from others. Vibrometry data were typically more consistent.

When lower frequencies were included in the feature set a considerable improvement in classification results was observed indicating that there is texture discriminant infor-

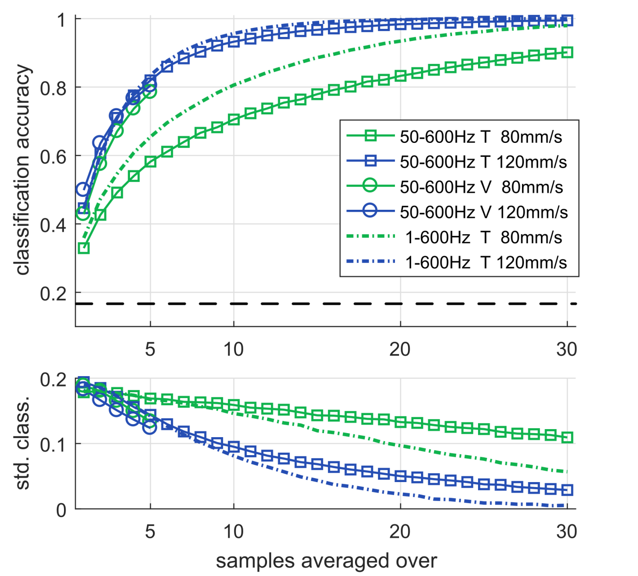

Fig. 4. Classification results based on 6 features extracted from texture spectra for both sets of data. Dashed black line represents chance classification. Bottom figure represents standard deviation of classification results.

mation in the 1-50 Hz frequency range. Our tribometer is capable of capturing a number of highly salient features, producing a classification accuracy of up to 84% (80% for vibrometry) when features extracted from five 120 mm/s swipes are used. Near-perfect classification results are observed for a set of 30 swipes collected at 120 mm/s as well as for feature sets containing low frequency components. To confirm the salience of these features, we tested them under the null hypothesis that they arise from a single distribution (instead of separate textures) and report the results in Fig. 5. Most of the features used for classification resulted in F-values corresponding to $.005<P<.05$. Moreover, the relative magnitudes of the F-values serves as a good approximation of relative classification results. Additionally, it is worth noting that DC friction is the most discriminant quality of

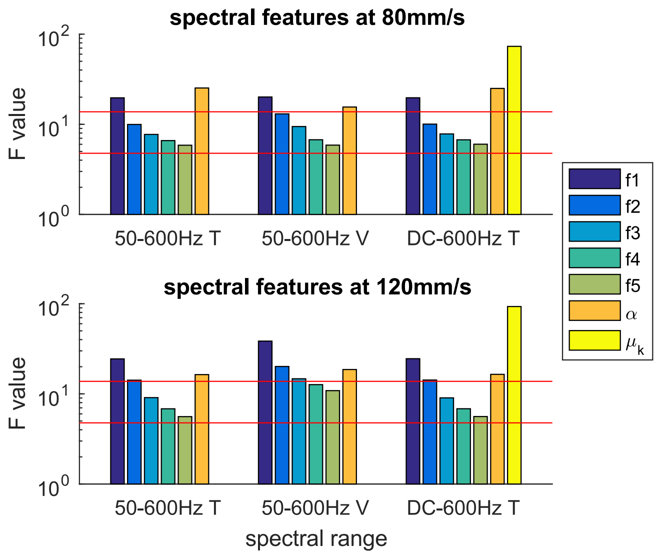

Fig. 5. F-test values for each of the 5 spectral features (f1-f5), the fitting parameter α extracted from both tribometry (T) and vibromtetry (V) data, and the kinetic friction coefficient μ_k . Red lines represent F-values at which p = .05 and p = .005 from bottom to top respectively. Note that μ_k was not used in any of the classifiers and is shown for reference.

textures across all features.

When filter statistics were used, the vibrometry data continued to outperform tribometry to a varying degree. Overall classification results in Fig. 6 suggests that variability in the both tribometry and vibrometry spectra is not just random, but that it contains texture-specific information. This is consistent with the hypothesis that variations in the spectra associated with touch are in fact perceptually relevant. Indeed, the importance of such variations has been firmly established in audition [15], so it is not altogether surprising to discover this in the tactile context. In terms of comparing the two measurement methods, it is evident that tribometry is able to capture some level of variation in spectra, but that it requires many more samples than vibrometry to achieve the same results for feature sets based on variance, skew and kurtosis. Vibrometry data also shows slight improvement in classification results with larger scanning speed, something that was observed in [1], however, the same trend is absent in tribometry data with results fluctuating drastically as a function of speed.

While the superior classification of vibrometry data may be ascribed in part to greater control over the speed and normal force of the scanning finger, the difference in classification results for higher order statistics points to factors in the underlying nature of data rather than protocol alone. The most intuitive explanation is that tribometry lateral force data does not capture local skin-texture interactions but instead sums the bulk contribution of contact points to the overall friction detected by the force sensor. In that fashion, much variation in envelopes may be blurred, hence still providing a good estimate of the envelope means but not their temporal variation. Because vibrometry is a highly localized measurement collecting the skin response due to actuation at the contact boundary it is not surprising that the modulation envelopes are captured to a better degree.

IV. Discussion

When a texture is explored by a human finger, local shear forces are elicited by the contact points between the skin and texture surfaces. These shear forces give rise to vibrations in the tissue which are known to be correlated to perception [1]. In this work, we have asked whether a direct measurement of the shear forces via tribometry might plausibly capture texture-specific information, and if so, how that information might be extracted. We tested the ability of two techniques – spectral features and band-pass filter statistics – to classify textures based on both vibrometry and tribometry. In general, the vibrometry data proved more highly discriminating, especially when employing higher-order band-pass filter statistics. Successful classifiers were also built upon tribometry data, however it is very clear that non-stationarity is not captured to the same degree of accuracy.

While these results do not establish the perceptual relevance of either tribometric measurements or band-pass filter statistics, they do encourage continued research, especially when considered in light of work in the auditory domain [15]. The work of McDermott and Simoncelli has shown unequivocally that statistics of modulation envelopes including the marginal moments considered here as well as auto- and cross-correlations, are perceptually significant. It is intriguing to note that, when computing the envelopes of band-passed texture data, many displayed cyclical behavior and could therefore be further analyzed in terms of correlations. Another implication of work presented here is that vibrometry and tribometry may each provide only part of the information necessary to parameterize natural texture for playback on friction modulation devices. Vibrometry fails to capture DC and low frequencies, while tribometry may blur the underlying vibration data. Perhaps a combined approach is called for.

V. Future Work

Our future work in this area includes one, gathering tribometry data for a larger set of textures; two, incorporating DC levels of lateral force (i.e., average friction), something that tribometry is uniquely positioned to measure, into the classification technique; three, incorporating additional filter statistics, especially auto and cross-correlations; four, comparing the clustering of band-pass filter statistics with perceptual clustering obtained through psychophysical experiments; and five, using filter statistics to synthesize artificial textures for display via surface haptic devices. This final point speaks to the long-term goal of our research: developing techniques for the recording and realistic playback of tactile textures.

VI. Acknowledgments

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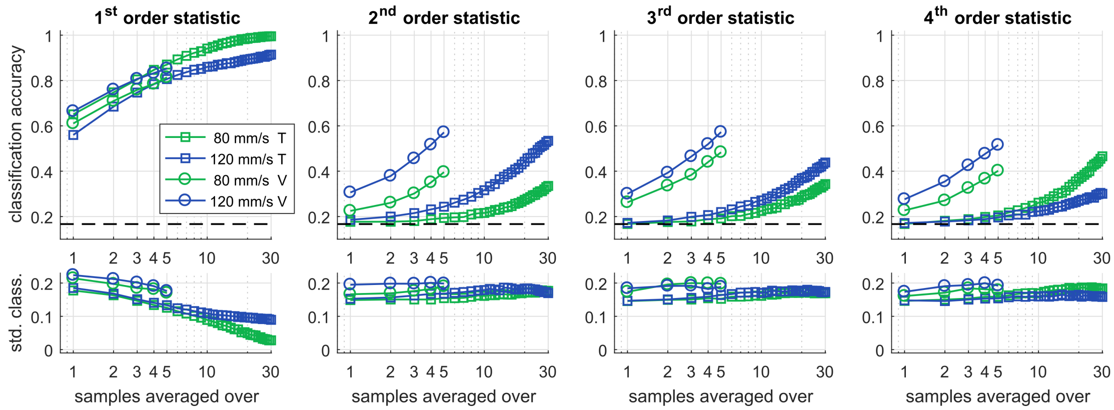

Fig. 6. Classification accuracy based on models built from four sets of characteristic features extracted from the envelopes of signals passed through a set of band-pass filters. Dashed black line represents chance level classification.

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