Roughness Encoding for Discrimination of Surfaces in Artificial Active-Touch

Calogero M. Oddo, Marco Controzzi, Student Member, IEEE, Lucia Beccai, Member, IEEE, Christian Cipriani, Member, IEEE, and Maria Chiara Carrozza, Associate Member, IEEE

Abstract—A 2 × 2 array of four microelectromechanical system (MEMS) tactile microsensors is integrated with readout electronics in the distal phalanx of an anthropomorphic robotic finger. A total of 16 sensing elements are available in a 22.3-mm² area (i.e., 72 units/cm²) of the artificial finger, thus achieving a density comparable with human Merkel mechanoreceptors. The MEMS array is covered by a polymeric packaging with biomimetic fingerprints enhancing the sensitivity in roughness encoding. This paper shows the ability of the sensor array to encode roughness for discrimination of surfaces, without requiring dedicated proprioceptive sensors for end-effector velocity. Three fine surfaces with 400-, 440-, and 480-μm spatial periods are quantitatively evaluated. Core experiments consisted in active-touch exploration of surfaces by the finger executing a stereotyped human-like movement. A time–frequency analysis on pairs of tactile array outputs shows a clustering of the fundamental frequency, thus yielding 97.6% worst-case discrimination accuracy with a k-nearest-neighbor (k-NN) classifier. Hence, surfaces differing down to 40 μm are identified in active-touch by both hardware and processing methods based on exteroceptive tactile information. Finally, active-touch results with five textiles (which differ in texture or orientation) are shown as a preliminary qualitative assessment of discrimination in a more realistic tactile-stimulation scenario.

Index Terms—Artificial touch, force and tactile sensing, microelectromechanical system (MEMS) sensors array, robotic finger, roughness encoding.

I. INTRODUCTION

The development of a tactile sensory system, which is able to mimic the human sense of touch in the encoding of textures and is compact enough to be integrated into articulated artificial fingers, would significantly improve dexterous manipulation (e.g., exploited in industrial, service, or assistive robotics) and upper limb prosthetics [1]–[3]. Within prosthetics, one of the main drawbacks of current commercial systems is the lack of sensory feedback [4]. As a consequence, the user is unable to feel an item held by the hand.

Among the various properties that an artificial tactile system should be able to sense, texture is one of the most challenging and less established. Considering the role that has been hypothesized in humans for high-density surface-located type-I mechanoreceptors [5], [6], gathering information on texture of a surface could take benefit from the implementation of artificial tactile systems that can encode dynamic events with a low threshold in sensitivity and a human-like spatial resolution of taxels [7]. In humans, texture has two major independent dimensions: roughness and softness [8]. Other surface qualities, such as stickiness, wariness, bumpyness, and harshness, were identified. However, these are not independent from the two major dimensions, and there is a consolidated agreement for a primacy of the smooth–rough dimension as a descriptor, even if not unique, of surface textures [8]–[10]. Therefore, taking inspiration from the human sense of touch, in this study, we focus on roughness, which is associated with the spatial modulation of the surface (i.e., spatial coarseness, at both macro- and microscales) [9], and in humans it is mediated by neural mechanisms which are also involved in tactile guidance during dexterous manipulation [5], [11].

The objective of this study is to develop an exploratory artificial finger equipped with tactile microsensors at its fingertip and a method for robust discrimination of surfaces based on roughness encoding during stereotyped movements. Such a system has not been presented so far and may be exploited in future next-generation hand-prostheses [12], [13], with the aim of providing noninvasive or invasive afferent sensory feedback.

To our knowledge, previous works for roughness encoding showed experimental results under passive-touch protocols only, i.e., surfaces were presented to a still sensorized fingertip that was not integrated into an actuated finger, or without relative movements of finger linkages in case of integration. Hosoda et al. developed a soft fingertip with a smooth surface embedding strain gauges and PVDF films in a random manner at different depths of the rubber layers, allowing for discrimination of five different types of materials [14]. Wettels et al. developed a tactile sensor array consisting of a rigid core surrounded by a weakly conductive fluid contained within an elastomeric skin. The sensor uses the deformable properties of the fingerpad, and tactile information relative to the contact force is retrieved from impedance measurements via embedded electrodes [15], [16]. Dynamic roughness encoding was shown via time–frequency inspection in [17], while manually moving the artificial finger over specimens, by means of a pressure sensor located away...
from the skin and functioning as a hydrophone in a fluid. A fingertip-shape tactile sensor integrating a microphone has also been investigated to quantify textural features [18] presented by medium-coarse stimuli producing a square wave that is 1 mm in height, with wavelength varying from 1 to 4 mm with 0.5-mm increments. A fingertip, which is three times larger than the human finger, was developed to provide information on roughness, stiffness, and friction of the object with which it comes into contact [19], [20]. Some other works presented the integration of tactile sensing in actuated robotic fingers, but the focus has mainly been on grasp stabilization rather than on the encoding of spatial coarseness. Examples include the Gifu III Robotic Hand [21] and the DLR Hand II [22] with embedded six-axis force sensors.

We previously presented a bioinspired fingertip with tactile sensors embedded in a viscoelastic packaging with medium-coarse fingerprints, which was suitable for the encoding of surface roughness in the frequency domain under controlled stimuli [23]. To provide the controlled stimuli, we [23] used a 2-degree-of-freedom (DoF) platform presenting tactile specimens to the sensor in a precise and repeatable manner; the fingertip was still, while surfaces were indented with controlled normal contact force and then stroked at known constant velocity tangentially to the fingerpad. Periodic ridged tactile stimuli (i.e., gratings), which can be considered as the kernel of everyday life surfaces, were selected as a class of standardized test surfaces. Gratings are widely used to investigate roughness encoding in neurophysiological studies [6], [24]. We demonstrated that they could be identified by means of spectral analysis on the outputs of the sensor array, since the constant-speed sliding motion of the grating resulted into a stationary fundamental frequency equal to the ratio between the tangential velocity and the spatial period of the scanned stimuli [23].

In this study, we use the same class of tactile stimuli, and we extend the passive grating-recognition method to the application of an active underactuated [25], [26] robotic finger (see Fig. 1) to emulate the possible behavior of a robotic or prosthetic hand in exploring objects. We integrate a 2 × 2 array of four tactile sensors (resulting in 16 channels in an area of 22.3 mm², i.e., 72 units/cm²) and biomimetic fingerprints in the distal phalanx of a robotic finger [see Fig. 1(a)] being appropriate for the integration within a hand prosthesis [27].

As a control condition, we present the fundamental-frequency modulation under a passive-touch protocol with controlled stimulus scanning velocity. Next, as an experimental condition, the robotic finger actively explores the samples in a predefined trajectory. Three gratings having very close spatial periods (i.e., 400, 440, and 480 μm) are evaluated to demonstrate the working principle and accuracy of the sensor array and its performance. Results demonstrate a surface-identification approach based on 1) the implementation of a stereotyped feedforward exploratory trajectory, 2) time-frequency analysis via wavelet transform (WT) and cross-wavelet transform (XWT) on the outputs of the tactile sensors, and 3) k-nearest-neighbor (k-NN) discrimination based on extracted fundamental frequency; this is bioinspired to sensorimotor control models [28], since it is based on planned-motion trajectory rather than continuous feedback from proprioceptive sensors.

This paper is organized as follows. Section II describes the developed finger. Section III details the roughness-encoding approach, the experimental protocol, and the wavelet-analysis technique. Section IV shows 1) passive-touch results, which demonstrate correct operation of the finger in a precisely controlled experiment, and 2) outcomes in an active-touch exploratory task. Finally, insights on future work 1) present the possibility to include phase differences from adjacent sensor outputs as a further discrimination feature and 2) shows preliminary active-touch experimental results with textiles (which differ in texture or orientation) as a proof of discrimination feasibility with everyday life surfaces.

II. MATERIALS

A. Underactuated Finger

The robotic finger [see Fig. 1(d)] was human-sized [29], tendon-driven (as given in [12], [13], and [27]), and underactuated, i.e., with more DoFs than actuators. Such property reduces
design complexity and allows self-adaptation and anthropomorphic movements similar to human exploratory tasks [12]. The finger had 3 DoFs (as flexion/extension DoFs of the human finger) and two dc-motor actuators (i.e., model 1727, Faulhaber Minimotor; ratio 14:1) under position control. One motor actuated the flexion/extension of the metacarpophalangeal (MCP) joint, and the other was for the underactuated flexion/extension of the proximal interphalangeal (PIP) and distal interphalangeal (DIP) coupled joints (as Hirose’s soft finger [30]).

B. Tactile Array

A 2 × 2, with 2.36-mm pitch, array of four microelectromechanical system (MEMS) sensors was connected to a rigid-flex board integrated in the distal phalanx of the robotic finger [see Fig. 1(a)]. The core microsensor [see Fig. 1(b)] is a 3-D high aspect ratio, ~1.4 mm³, MEMS resulting from silicon microstructuring technologies [31]. Each sensor integrated four piezoresistors at the roots of a cross-shape structure equipped with a mesa. This turned out into a 16-channel sensory system for transducing the mechanical interaction with external tactile stimuli in a 22.3-mm² area of the fingerpad [see Fig. 1(a)]. Therefore, a density of 72 units/cm² (i.e., 16 channels/22.3 mm²) was reached, which is similar to the 70 units/cm² of human Merkel mechanoreceptors [32] which have been shown to encode roughness in studies with monkeys [5].

The sensors of the array are labeled as S1, S2, S3, and S4 according to Fig. 1(a), while the outputs of each sensor are labeled as P1, P2, P3, and P4, as shown in Fig. 1(b). P1 and P3 are related to piezoresistors implanted on the cross-shape structure on tethers oriented across the finger axis, while P2 and P4 are on tethers oriented along the finger axis. The output signals were acquired at \( f_s = 300 \text{ Hz} \) without preamplification by means of a 16-channel 24-bit analog-to-digital converter (ADS1258, Texas Instruments) lodged in the distal phalanx.

The packaging of the MEMS tactile array mechanically filters the physical stimulation applied to the fingertip and is crucial to its biopsensed response. It is known from previous studies that fingerprints enhance tactile sensitivity [33]–[35]. Therefore, the outer packaging layer of the fingertip, which is made of synthetic compliant material (DragonSkin, Smooth-On), had a surface with fingerprints [see Fig. 1(c)] mimicking the human fingerpad. To achieve biomimetics [36], the fingerprints had 400 µm between-ridge distance; their curvature radius was set to 4.8 mm in the center of the sensor array [see the red ridge in Fig. 1(c)], while the artificial epidermal ridge had a height of 170 µm, and the total packaging thickness from the mesa structure of the silicon microsensor was 770 µm.

C. Experimental Setup

The experimental setup consisted of two main subsystems, as shown in Fig. 1(d): the sensorized robotic finger and a platform under horizontal [see the y-axis in Fig. 1(d)] position/velocity control, which was a simplified version of a 2-DoF platform [37] used in previous studies [23], [38]. Changeable gratings were housed in a carrier of the platform. A load cell (Nano43, ATI, NC) was integrated under the carrier to verify that finger–stimulus contact forces were in the range of hundreds of milliNewtons, such as that occurring in typical human tactile exploratory tasks [24].

III. METHODS

A. Fundamental Frequency

When a relative motion at speed \( v(t) \) occurs between a finger and a grating having spatial period \( \Delta p \) along the motion direction, a correct roughness encoding by the tactile sensor array should reveal a fundamental tone at frequency \( f_{\text{prime}}(t) \) [37]

\[
 f_{\text{prime}}(t) = \frac{v(t)}{\Delta p}. \tag{1}
 \]

B. Experimental Protocol

The coherence between the theoretical [see (1)] and the experimental fundamental frequency is demonstrated at first in passive-touch; stimuli were stroked at controlled known velocity in order to show and evaluate the encoding principle [see (1)] under a protocol allowing to directly decouple the contribution of velocity \( v(t) \) from stimulus spatial coarseness \( \Delta p \). In a second set of experiments, the approach was evaluated under an active-touch protocol with the robotic finger mimicking the natural exploratory movement by the hand and without measuring the instant sliding velocity. In order to evaluate their discrimination by the artificial finger, three gratings (see Table I) with 400-, 440-, and 480-µm spatial periods \( \Delta p \) were used eight times each with both the protocols, for a total of 48 experiments (runs). The tested spatial periods are in the range of studies on roughness discrimination in humans [38]. Preliminary active-touch experiments were performed with textiles as well and are presented as insights on future work in Section V-B.

1) Passive-Touch Experiments With Gratings: The finger was flexed and the fingertip brought into contact with the tactile stimulus [see phases 1 and 2 of Fig. 1(d)]. To show the fundamental frequency dynamically modulating as a function of velocity, a double-ramp sliding motion was then applied to the grating along the positive y-axis [see phase 3a of Fig. 1(d)] via the platform under position/velocity control: a 10-mm ramp for 1500 ms (\( v_1 = 6.7 \text{ mm/s} \)) was followed by a 10-mm one in 1000 ms (\( v_2 = 10.0 \text{ mm/s} \)). This protocol is named passive-touch since the robotic finger is still during the stimulus-sliding motion. Based on (1), Table I shows the theoretical fundamental

<table>
<thead>
<tr>
<th>Stimulus spatial period ( \Delta p )</th>
<th>( 400 \mu m ) (runs 1–8)</th>
<th>( 440 \mu m ) (runs 9–16)</th>
<th>( 480 \mu m ) (runs 17–24)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stimulus sliding velocity ( v )</td>
<td>( v_1 = 6.7 \text{ mm/s} )</td>
<td>( 16.7 \text{ Hz} )</td>
<td>( 15.2 \text{ Hz} )</td>
</tr>
<tr>
<td>( v_2 = 10.0 \text{ mm/s} )</td>
<td>( 25.0 \text{ Hz} )</td>
<td>( 22.7 \text{ Hz} )</td>
<td>( 20.8 \text{ Hz} )</td>
</tr>
</tbody>
</table>
frequencies, ranging from 13.9 to 25.0 Hz, in the passive-touch protocol depending on the combination of sliding velocity and tactile stimulus.

2) Active-Touch Experiments With Gratings: Active-touch experiments were implemented by controlling the MCP joint to contact the tactile stimulus [see phases 1 and 2 of Fig. 1(d)]; subsequently, the PIP and DIP joints were flexed [see phase 3b of Fig. 1(d)] to scan, along the negative y-axis, the same spatial portion of stimulus presented with the passive-touch experiments. The finger was actuated to perform a smooth human-like exploratory task lasting for 2 s. The same pattern was provided to the finger for all the active-touch runs, thus implementing a stereotyped [14] exploratory movement.

C. Data Analysis

1) Wavelet and Cross-Wavelet Transforms: The elaboration method should take into account that in the active-touch experiments the end-effector velocity could be time variant. As a consequence, the fundamental frequency would dynamically modulate within each exploratory session, while rubbing the surface. To allow retrieving such dynamic frequency-modulation, the continuous WT is used, thus expanding the output signals from the sensor array into a time–frequency space. Data analysis is performed via the MATLAB wavelet-coherence package (for underlying theory and an application example, see [39]); the default Morlet wavelet function and 100 scales per octave were selected. More reliably than the single-channel WT, the cross WT (XWT) is applied to identify time–frequency regions with high common power between outputs from different sensors of the array, hence establishing a robust elaboration method based on combined processing of pairs of sensor outputs.

Each sensing-element (i.e., piezoresistor) response depends on its orientation with respect to the applied stimulus [31]. Although the MEMS sensor is suitable (both bare [31], [40], or packaged [41]) to solve the contact force, in this study, the raw voltage readings were used. This represents an added value of the system, not only because the contact force is not addressed in this study, but mainly because this turns out into a technique being more robust and less time-consuming for the operator (thereby avoiding periodic recalibration operations). The 16 sensing elements of the array are either aligned in the direction across the finger or along the finger. The analysis via XWT is operated by processing outputs of piezoresistors that are oriented along the same direction. Specifically, of the 16 available channels, three are shown in the following to point out the meaningful information available by processing in combination a pair of outputs belonging to sensors in line across the finger axis [i.e., P1 outputs from sensors S1 and S2, according to the labeling of Fig. 1(b) and (c)] and a pair of outputs from sensors aligned along the finger axis (i.e., P1 outputs from sensors S4 and S1).

The application of the WT and the XWT is graphically represented with colors mapping the normalized power in time–frequency space, where the 5% significance level is highlighted as a thick contour. In addition, the XWT provides information about the local relative phase differences between sensor outputs. Phase information obtained via XWT \((O_1, O_2)\) is graphically represented by arrows pointing right or left if the signals are in-phase or in anti-phase, pointing down if sensor output \(O_1\) leads \(O_2\) of \(\pi/2\), and pointing up if \(O_2\) leads \(O_1\).

2) Passive-Touch Roughness Encoding Via Vibratory Cues: To discriminate the gratings via vibratory cues [from (1)], the frequency \(f_{\text{MP}}\) carrying the maximum power was identified, as a function of time \(t_k\), from the XWT applied to pairs of array outputs (which are labeled as \(O_1\) and \(O_2\) for the sake of generalization)

\[
\text{arg} \max_{t_k} |\text{XWT}(O_1, O_2)(t_k, f)|. \tag{2}
\]

In passive-touch, the vibrational encoding was expected to last for the entire stimulus sliding. Hence, the frequency \(f_{\text{MP}}\) should encode the spatial coarseness of the stimuli whatever be the time instant \(t_k\), provided that it belonged to the sliding motion at controlled constant velocity.

The mean value \(f_{\text{MP}}(O_1, O_2)\) of the frequency \(f_{\text{MP}}\) carrying the maximum power was calculated on two pairs of array channels (i.e., P1S1–P1S2 and P1S4–P1S1). This was calculated from significant signal slices on each run; in particular, 200 sample windows (with 667-ms duration) were extracted from the 6.7 and 10.0 mm/s sliding motion in order to consider subsets of data belonging to constant-speed phases of the passive-touch protocol. Due to the constant sliding velocity of surfaces, a clustering of \(f_{\text{MP}}\) data is expected subject to spatial coarseness encoding being suitable for discrimination of surfaces. Statistical indices on frequency \(f_{\text{MP}}\) were calculated across repeated runs (with same grating): double mean \(\bar{f}_{MP}(O_1, O_2)\) and standard deviation \(\Delta f_{\text{MP}}(O_1, O_2)\) aggregating the eight windows of \(f_{\text{MP}}\) across the repeated runs (per grating and velocity), mean-max \(\text{Max}(O_1, O_2)\), and mean-min \(\text{Min}(O_1, O_2)\) (i.e., the mean across the repeated runs of the maximum/minimum \(f_{\text{MP}}\) registered within each window). In passive-touch, the grating was identified by selecting the one yielding in minimum error between theoretical (see Table I) and experimental fundamental frequency.

3) Active-Touch Roughness Encoding Via Vibratory Cues: While in passive-touch the vibrational roughness encoding is expected to last for all the sliding of the stimulus, in active-touch, it is expected that each unit of the array best encodes the tactile stimulus in a subset only of the finger exploratory task. In fact, the varying inclination of the fingertip in active-touch generally results in a shift of the center of pressure on the fingerpad. Therefore, it is crucial to identify significant regions in time–frequency space. To this aim, the instant \(t_{\text{MP}}\) corresponding to the maximum cross-power between adjacent units is identified run by run from \(f_{\text{MP}}\) [as defined in (2)] as a starting point for active-touch data analysis

\[
t_{\text{MP}}(O_1, O_2) = \text{arg} \max_{t_k} |\text{XWT}(O_1, O_2)(t_k, f_{\text{MP}}(O_1, O_2)(t_k))|. \tag{3}
\]

The mean value \(\bar{f}_{\text{MP}}(O_1, O_2)\) of the maximum power frequency \(f_{\text{MP}}\) was calculated run by run on two pairs of array channels (i.e., P1S1–P1S2 and P1S4–P1S1) from a
The latter condition is a worst-case evaluation because the sliding motion stops at $t_3 = 3.0$ s. Vibrational encoding of stimulus spatial period is appreciated between $M$ time intervals that were in strict accordance with the expected ones (see Table I). A lookup table, based on theoretical fundamental frequencies (see Table I) and thresholds, guarantees 100% success in classifying the gratings down to the tested 40 μm difference in spatial coarseness.

### B. Active-Touch Experiments With Gratings

The active stereotyped exploratory task presented a subset lasting about 150 ms, during which the spatial coarseness of the tactile stimuli was encoded with vibrational features by, at least, one unit of the array (cf., Fig. 4). An overlap of about 80 ms was observed [see Fig. 4 (right)] for the combined vibrational activation of distal sensor units (i.e., S1 and S2) and proximal sensor ones (i.e., S3 and S4, with the former not shown for the sake of graphical clearness). Fig. 5 shows WT and XWT applied to P1S4, P1S1, and P1S2, and $M_{MP}$ resulting from the analysis of signals gathered by pairs of sensor outputs. The shifting of the high-power red zone toward higher frequencies reveals that the end-effector velocity varied (increasing) with time, while rubbing the sample. Variation of end-effector velocity within each active-touch rub is also confirmed by the higher values of the standard deviation of $f_{MP}$, which was at most 8.3% of its mean value (5.5 Hz/65.9 Hz; see Table III), and higher difference between $\overline{M}_{MP}$ and $\overline{f}_{MP}$ indices, in comparison with the constant-velocity passive-touch tests (see Table II).
**Fig. 3.** WT on single channels (i.e., P1S4, P1S1, and P1S2) of the array and XWT on channel pairs P1S4–P1S1 and P1S1–P1S2. The plots focus on the velocity step during the passive-touch presentation of the 480-μm stimulus to the robotic finger, showing the frequency shift from 13.9 to 20.8 Hz according to (1). High-power regions in time–frequency space are colored in red. The thick contour surrounding the red region identifies the 5% significant level. The arrows in the XWT plots are a graphical representation of the phase difference between the pairs of channels (pointing right: in-phase; left: antiphase; down: series 1 leading series 2 by 90°).

<table>
<thead>
<tr>
<th>Statistical index</th>
<th>O1</th>
<th>O2</th>
<th>Stimulus spatial period Δp (μm)</th>
<th>400 μm runs 1-8</th>
<th>440 μm runs 9-16</th>
<th>480 μm runs 17-24</th>
</tr>
</thead>
<tbody>
<tr>
<td>f_{MP}(O1,O2) (Hz)</td>
<td>P1S1</td>
<td>P1S2</td>
<td>16.6</td>
<td>25.0</td>
<td>15.1</td>
<td>22.8</td>
</tr>
<tr>
<td>Δf_{MP}(O1,O2) (Hz)</td>
<td>P1S1</td>
<td>P1S2</td>
<td>0.2</td>
<td>0.3</td>
<td>0.1</td>
<td>0.2</td>
</tr>
<tr>
<td>Δf_{MP}(O1,O2) (Hz)</td>
<td>P1S4</td>
<td>P1S1</td>
<td>0.1</td>
<td>0.4</td>
<td>0.1</td>
<td>0.2</td>
</tr>
</tbody>
</table>

**Fig. 7** shows a plot of the 20 samples subset per run of f_{MP}(P1S4, P1S1) and f_{MP}(P1S1, P1S2) around t_{MP}(P1S4, P1S1) and t_{MP}(P1S1, P1S2), as defined in (2) and (3). The fundamental frequency f_{MP}, as shown in Fig. 7, is monotonically modulated from a lower value to a higher one, due to the increasing nonconstant speed, within each run in the considered 20 samples. Despite of overlap of instant fundamental frequencies f_{MP} arising in active-touch with different gratings, Fig. 7 reveals a clear separation among the three tactile stimuli, as indicated by the black dots representing the mean fundamental frequency f_{MP} run by run per couple of sensor outputs. This is more evident in the scatter plot of f_{MP} values resulting from the two considered channel pairs (cf., Fig. 8), which reveals a clear clustering of the grating spatial period Δp and reduced variance Δf_{MP} (across the repeated runs) of the mean fundamental frequency, as confirmed by the depicted ellipses in Fig. 8. It is significant to point out that, coherently with the physical model underlying (1), finer grating spatial periods Δp resulted in higher frequencies in both the axes of Fig. 8. Due to high repeatability, a k-NN classification applied to data of Fig. 8 guaranteed excellent discrimination performance (see Table IV). A 97.6% identification accuracy was obtained in the worst-case training based on a single run per stimulus and the other runs used as validation set (i.e., leave-21-out). The accuracy raised to 100%
with all the gratings by using at least four runs per stimulus as a training set (i.e., leave-12-out).

Velocity was constant and known (either 6.7 or 10.0 mm/s was tested) in passive-touch experiments, while in active-touch, it was not directly measured. However, as a final evaluation of tested velocity range in comparison with typical human exploratory tasks, we can reconstruct this information by inverting (1) via the knowledge of tested stimuli and measured $\overline{Mf}_{MP}$ and $\overline{mf}_{MP}$ indices (see Table III), thereby resulting in active-touch velocities monotonically increasing approximately from 22 to 31 mm/s within the significant portion (which is around $t_{MP}$) of each run. Thus, the tested velocities belong to the wide range (from a few millimeters per second up to more than a hundred of millimeters per second) used, with no significant related effect on perceived roughness, by humans during active exploratory tasks [42].

A compared inspection of the three time-domain plots aligned vertically in Fig. 6 confirms that a change in the grating spatial
TABLE III

<table>
<thead>
<tr>
<th>Statistical index</th>
<th>O1 O2</th>
<th>Grating spatial period $\Delta p$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>400 $\mu$m (runs 1-8)</td>
</tr>
<tr>
<td>$\tilde{f}_{MP}(O1,O2)$ (Hz)</td>
<td>P1S1 P1S2</td>
<td>65.9</td>
</tr>
<tr>
<td>$\Delta f_{MP}(O1,O2)$ (Hz)</td>
<td>P1S1 P1S2</td>
<td>5.5</td>
</tr>
<tr>
<td>$Mf_{MP}(O1,O2)$ (Hz)</td>
<td>P1S1 P1S2</td>
<td>75.9</td>
</tr>
<tr>
<td>$mf_{MP}(O1,O2)$ (Hz)</td>
<td>P1S1 P1S2</td>
<td>57.2</td>
</tr>
</tbody>
</table>

Fig. 6. Active-touch vibrational frequency encoding in time domain of the grating spatial period $\Delta p$ by sensor outputs P1S1, P1S2, and P1S4. Moreover, P1S1 and P1S2 are always in-phase, while the phase difference with P1S4 varies, depending on the surface (as confirmed by the horizontal shift of the blue trace with respect to the red and green ones, while comparing the plots for the three values of the grating spatial period $\Delta p$), coherently with (4).

period $\Delta p$ causes a modulation of the vibrational cues in active-touch.

V. INSIGHTS ON FUTURE WORK

A. Toward Surface Classification With Nonstereotyped Exploratory Movements: Phase Locking

Phase information was taken into account as a further feature in addition to the fundamental frequency useful for discriminating among surfaces. A qualitative discussion of related results is presented here as a preliminary study for future works addressing passive-touch experiments without the limiting condition on constant (or known) stimulus-velocity or active exploration of surfaces under general nonstereotyped trajectories.

Considering piezoresistors belonging to sensor tethers that are oriented along the same direction, we expect the gathered output signals to show vibrational components having a phase difference $\Delta \varphi_{i,j}$ being independent on the stimulus sliding-velocity

$$\Delta \varphi_{i,j} = \frac{2\pi}{\Delta p} \frac{\Delta y_{j,i}}{\Delta p}$$

where $\Delta y_{j,i} = y_i - y_j$ is the difference of the $y$-coordinates of sensor $S_i$ and sensor $S_j$ (while considering sensors aligned along the finger axis, i.e., S1–S4 and S2–S3, $\Delta y_{j,i}$ corresponds to the 2.36 mm pitch of the array in case that the plane of the
TABLE IV
PERCENT DISCRIMINATION ACCURACY WITH GRATINGS AS TACTILE STIMULI, VIA k-NN CLASSIFICATION AND LEAVE-M-OUT VALIDATION (SEE SECTION III-C3)

<table>
<thead>
<tr>
<th>Grating spatial period Δp</th>
<th>400 μm (runs 1-8)</th>
<th>440 μm (runs 9-16)</th>
<th>480 μm (runs 17-24)</th>
</tr>
</thead>
<tbody>
<tr>
<td>M=3,6,9,12 (1.4 runs out x 3 surfaces)</td>
<td>100.0%</td>
<td>100.0%</td>
<td>100.0%</td>
</tr>
<tr>
<td>M=15 (5 runs out x3 surfaces)</td>
<td>100.0%</td>
<td>99.9%</td>
<td>100.0%</td>
</tr>
<tr>
<td>M=18 (6 runs out x3 surfaces)</td>
<td>100.0%</td>
<td>99.3%</td>
<td>99.8%</td>
</tr>
<tr>
<td>M=21 (7 runs out x3 surfaces)</td>
<td>100.0%</td>
<td>97.6%</td>
<td>99.3%</td>
</tr>
</tbody>
</table>

sensors is parallel to the stimulus), according to the labeling introduced in Fig. 1(a). This results in signals always in-phase if considering the couple S1–S2 or the couple S3–S4 and with phase differences depending on the tactile stimulus for the other combinations.

In passive-touch, during finger–stimulus contact, sensors S1 and S2 of the array on the distal part of the phalanx were simultaneously aligned under the same ridge of each grating [same y-coordinate, i.e., Δy_1,2 = 0, according to the reference frame in Fig. 1(d)]. Therefore, coherently with (4), the outputs from piezoresistors belonging to sensor tethers which are oriented along the same direction (e.g., P1S1 and P1S2), were in-phase for all the runs, regardless of the grating spatial period. This is also confirmed in time domain in Fig. 2 (in-phase P1S1 and P1S2 signals) and depicted by the horizontal arrows in time–frequency space of the XWT(P1S1,P1S2) plots in Fig. 3. Conversely, a phase difference was observed from sensor units lodged at different positions along the axis of the finger (e.g., P1S1 and P1S4, which are represented with red and blue traces in Fig. 2 and with arrows in the second subplot of Fig. 3). Velocity had no effect on the phase relationships, as shown by the arrows before and after the velocity variation at t_2 = 2.0 s in Fig. 3. This property of phase locking is coherent with (4) (since no velocity appears in the equation) and can be applied to remove the velocity dependence of (1). However, a problem occurs with respect to (4): Phase differences can be experimentally measured only in a 2π range, thus introducing limiting conditions to invert (4) (i.e., Δp > 2Δy_pitch = 4.72 mm or Δp > Δy_pitch = 2.36 mm, depending on the knowledge of the sign of the relative finger–stimulus velocity). This means that, by just considering two spatially located sensors of a regular array, phase differences can be analytically reconstructed only in case that two sensors are encountered along the rubbing direction within a half- or full-spatial wavelength of the tactile stimulus. Such limiting conditions for spatially distributed sampling are equivalent to the Nyquist theorem for time-domain sampling.

Gratings with different spatial period Δp caused a modulation in the relative phase between units lodged along the direction of the finger axis (e.g., S4 with respect to S1 and S2) in active-touch as well. Consistently with (4), the phase difference between units...
aligned across the finger axis (e.g., S1–S2, with $\Delta y_{1,2} = 0$ mm) did not modulate. As an example from two couples of outputs from the array in both time (i.e., inspecting the relative timing between vibratory peaks in Fig. 4) and time–frequency (i.e., inspecting the arrows in Fig. 5) domains, the signals from P1S1 and P1S2 were in-phase, while a phase difference was observed between P1S4 and P1S1. The same behavior is shown in Fig. 6 for all the three used gratings (varying in $\Delta p$), as confirmed by the horizontal shift of the blue trace with respect to the red and green ones. It is relevant to point out that the phase relationships around the red high-power time–frequency regions (i.e., around $b_{311}$), as depicted for active-touch in Fig. 5, were consistent with the passive-touch ones (cf., Fig. 3). This is observable by comparing the arrows (equal down-right pointing) in the significant regions of the two figures. Further related results and considerations are left to future works.

B. Active-Touch Experiments With Textiles

Five textiles were tested in active-touch to preliminarily evaluate discrimination suitability in a more realistic tactile-stimulation scenario with respect to gratings. The five surfaces were a fine-denim cut along two different orientations [see Fig. 9(a) and (b)], a coarse-denim cut along two different orientations [see Fig. 9(c) and (d)], and a nap textile [see Fig. 9(e)]. The active-touch protocol detailed in Section III-B2 was used. For all the runs and textiles, the XWT was calculated on channel pairs to inspect data. Fig. 9 depicts one XWT [P1S1, P1S2] example for each textile. Each surface showed a repeatable specific pattern in time–frequency space in all the eight runs. Such repeatability was confirmed calculating the correlation indices for each time-domain raw single-sensor output over all the combinations of pairs of repeated runs with the same textile. As an example, average correlation coefficients for channel P1S1 over repeated runs are 0.96 $\pm$0.01 for textiles A and E, 0.97 $\pm$0.01 for textiles B and C and 0.98 $\pm$0.01 for textile D. All the coefficients are very close to one with a significant confidence interval, thereby demonstrating high repeatability and, thus, confirming the suitability for the discrimination of realistic surfaces. Moreover, average correlation coefficients lower in a range between 0.78 and 0.90, with significant confidence as well, while considering combinations of runs related to pairs of different stimuli.

Textiles present a surface structure being more complex and realistic with respect to gratings. Therefore, a number of spectral components rather than a single fundamental frequency should be taken into account in order to yield high classification performance (up to the full time-varying spectrum to succeed in the discrimination of unspecified tactile stimuli having a very complex surface structure). The extension and generalization of the discrimination technique presented for gratings in Section IV-B will be investigated in future works. Sandpaper tactile stimuli will be experimented as well: despite the fact that sandpaper is not usual in everyday-life tactile experience in comparison with textiles, it represents a significant testbed (as is confirmed by related psychophysical studies [24]) due to its aperiodic, but still standardized (grit size), surface structure.

VI. Conclusion

The vibratory patterns recorded by the sensor array during the sliding motion of gratings at known constant velocity coherently modulated at the expected frequency in passive-touch. The significant results shown under the passive-touch protocol constituted the foundations for the subsequent active-touch investigation. The XWT on outputs from adjacent sensors of the array revealed a fundamental spectral component being a function of time when the robotic finger actively explored the tactile stimuli. Despite of the nonconstant scanning velocity, the finger stereotyped exploratory-movement allowed to encode the spatial coarseness of gratings by identifying, in a 67-ms window (i.e., 20 samples at 300 Hz) of time–frequency space, the set of spectral components conveying the highest cross power between adjacent sensors.

This study showed the capability to discriminate among surfaces having spatial periods differing down to 40 $\mu$m, both under passive-touch and under human-like active-touch tasks. Performance in the active-touch discrimination of gratings was excellent, with worst-case accuracy (97.6%; see Table IV) being much higher than the one-third performance in case of random choice. Therefore, the 40-$\mu$m threshold underestimates the potential performance, and the developed technology could ensure better results while being tested with finer stimuli.

The evaluation of the robotic finger was operated with contact forces and velocities in the range used by humans during tactile exploratory tasks. In active-touch experiments with gratings, exteroceptive information (i.e., tactile cues) was enough for the successful coarseness encoding (see Figs. 4–8) and discrimination of surfaces (see Table IV), without the need to consider proprioceptive data (such as end-effector velocity). This could open various possibilities, while pursuing the integration of the developed artificial touch technology into an upper limb prosthesis via noninvasive (e.g., vibrating tactors [43]) or invasive (e.g., direct peripheral neural feedback [44], [45]) interfaces.

The proposed method is neither temporal nor spatial; rather, it is spatiotemporal because it is based on the temporal (i.e., vibrational) roughness encoding by each single sensor and on the combined observation by spatially adjacent units of the array to identify the data subset to focus on for analysis. Phase information (see Section V-A) via neighboring observers distributed on the surface of the fingerpad is associated with spatiotemporal variation as well.

Preliminary experimental results presented in Section V-B with textiles are promising, and future experiments will be oriented toward a quantitative analysis of discrimination accuracy with a wide set of everyday-life surfaces.

In future works, we will investigate more on how to implement classification techniques based on the phase locking between signals gathered by adjacent sensors of the array; to this aim, a smartly distributed sensor array and phase locking could be applied to emulate the hypothetical human model for coincidence detection shown in [11]. Attention will be paid to smart irregular physical positioning of sensor units, by getting design inputs from the biological model. This would allow to obtain a system of multiple phase relationships to solve, under
general unconstrained exploratory motions, spatial features being finer than the NN spacing of tactile units, as it happens in humans [5]. Therefore, following our aim while moving from passive to stereotyped active-touch protocols, phase relationships could be introduced as a further classification feature to go toward less-structured experimental conditions without requiring the exploratory movement to be stereotyped.

ACKNOWLEDGMENT

The authors thank N. Vitiello, F. Mattioli, R. Di Leonardo, and C. Filippeschi (Scuola Superiore Sant’Anna) and M. Mitulla and S. Schmitt (Institute of Microtechnology, Mainz) for technical support. Valuable conversations with J. Wessberg (Department of Physiology, University of Gothenburg) and with L. Pape (Dalle Molle Institute for Artificial Intelligence, Lugano) are gratefully acknowledged. The experimented tactile stimuli were provided by S. Johnson and B. Ranken (Unilever R&D, Port Sunlight). Crosswavelet and wavelet coherence software were provided by A. Grindested.

REFERENCES

Marco Controzzi (S’10) received the M.Sc. degree in mechanical engineering from the University of Pisa, Pisa, Italy, in 2008. He is currently working toward the Ph.D. degree in biorobotics with the Scuola Superiore Sant’Anna, Pisa. In June 2006, he joined the Advanced Robotics Technology and Systems (ARTS) Laboratory, Scuola Superiore Sant’Anna, Pisa, as a Research Assistant. He is a Cofounder of one of the spin-offs of the Scuola Superiore Sant’Anna. He is an author or coauthor of ten peer-reviewed scientific papers and two patents. His current research interests include the mechanical design of anthropomorphic robotic and prosthetic hands and arms and analytical models for grasping and manipulation.

Mr. Controzzi won the 2009 Antonio d’Auria Award (open to European citizens) from the Italian Robotics and Automation Association.

Maria Chiara Carrozza (M’04–A’06) received the M.Sc. degree in physics from the University of Pisa, Pisa, Italy, in 1990 and the Ph.D. degree in bioengineering from Scuola Superiore Sant’Anna, Pisa, in 1994. She is currently a Professor of biomedical engineering and robotics, and since 2007, she has been the Director of the Scuola Superiore Sant’Anna. She was a Visiting Professor with the Technical University of Wien, Wien, Austria. She is a member of the Scientific Committee of the Italy–Japan Joint Laboratory, ROBOCASA, Waseda University, Tokyo, Japan. Her current research interests include biorobotics, rehabilitation robotics, artificial hands, and tactile sensing. She has authored or coauthored more than 60 papers on ISI Journals, 100 papers in referred conference proceedings, and 12 patents.

Prof. Carrozza is a member of the IEEE Engineering in Medicine and Biology Society and the Italian Robotics and Automation Association.

Lucia Beccai (M’08) received the Laurea degree in electronic engineering from the University of Pisa, Pisa, Italy, in 1998 and the Ph.D. degree in microsystems engineering from the University of Rome Tor Vergata, Rome, Italy, in 2003. Since 1999, she has performed research at both the Center for Research In Microengineering and ARTS laboratories of Scuola Superiore Sant’Anna, Pisa, where, from 2008, she had a temporary position of Assistant Professor of bioengineering. She contributed to many international projects and was responsible for research management activities in several of them, addressing investigations related to biomedical microsystems for in-vivo applications, microelectromechanical systems, bioinspired solutions for bionic hand sensory feedback systems, the understanding of human tactile encoding mechanisms, and the development of artificial systems that can mimic selected tactile functionalities. Since 2009, she has been Team Leader at the Center for MicroBioRobotics@SSSA of Istituto Italiano di Tecnologia, Pontedera, Pisa, Italy, and her current scientific interests are related to the investigation of innovative sensing, actuation, and locomotion strategies in robotics using inspiration from Nature. Focus is on soft-bodied microrobot, biomimetic tactile sensors, and bio-hybrid sensing systems at the microscale. She is the author and co-author of several articles on refereed international journals and of more than 30 papers published in international conference proceedings.

Dr. Beccai is member of the IEEE Engineering in Medicine and Biology Society and the IEEE Robotics and Automation Society.

Christian Cipriani (S’06–M’09) received the M.Sc. degree in electronic engineering from the University of Pisa, Pisa, Italy, in 2004 and the Ph.D. degree in biorobotics from the Institutions Markets Technologies Institute for Advanced Studies, Lucca, Italy, in 2008. He is currently an Assistant Professor of biomedical robotics with The BioRobotics Institute (which was formerly called the ARTS and CRIM Laboratories), Scuola Superiore Sant’Anna, Pisa. He is a Founder of a spin-off company. His current research interests include mechatronic, controllability, and sensory feedback issues of dexterous robotic hands to be used as mind-controlled prostheses.

Dr. Cipriani is a member of the IEEE Robotics and Automation Engineering in Medicine and Biology Societies. He won the d’Auria Award in 2009 for prototypes of innovative robotic devices to aid the motor disabled from the Italian Robotics and Automation Association.

Calogero M. Oddo was born in 1983. He received, all cum laude, the B.Sc. degree in 2005 and the M.Sc. degree in 2007 in electrical engineering from the University of Pisa, Pisa, Italy, and the first- and second-level degrees, in 2006 and 2009, respectively, in industrial and information engineering from the Scuola Superiore Sant’Anna, Pisa, where he is currently working toward the Ph.D. degree in biorobotics. In 2006, he participated in the Ninth European Space Agency (ESA) Student Parabolic Flight Campaign, and in 2008, he participated in the First ESA Lunar Robotics Challenge. His current research interests include human and artificial tactile sensing. He has authored or coauthored 21 peer-reviewed scientific papers (with six in ISI journals) and extended abstracts.

Mr. Oddo won the Biorobotics prize, which was established by the Alumni Association of Scuola Superiore Sant’Anna, for his B.Sc. thesis. He was finalist for the Best-Student-Paper Award at the IEEE RoboBio09 conference.