Spectral Template Based Classification of Robotic Whisker Sensor Signals in a Floor Texture Discrimination Task.

Mat Evans[1], Charles W. Fox[1], Martin J. Pearson[2] and Tony J. Prescott[1]

***Abstract*—**

Whisker-based floor texture classifications could form an important input to mobile robots for use in navigation and object recognition, especially in harsh and covert environments. Previous work [9], [11], [13] showed that artificial whiskers can be used for texture discrimination in controlled situations. In these experiments both the movement of the whisker and the textures used were carefully selected to constrain the problem. In contrast, the present study investigates whiskered texture discrimination in a practical, real-world task. An artificial whisker was attached to an iRobot Roomba vacuum cleaner, and its base displacement was sampled while the robot moved in different directions on four different real-world floor surfaces: rough and smooth carpet, vinyl and tarmac. Surface discrimination is possible using a template based classifier. The discrimination is dependent on knowing robot motion type, with different movement strategies providing better signals for certain texture discriminations.

I. Introduction

The rat whisker system has been the subject of a great deal of biological research [1], [7], [15], [5]. Numerous behavioural experiments have determined that rats are tactile discrimination specialists, both of object location in the whisker field [20], [21] and especially of surface texture [3], [4]. In the dark, rats can extract the identity of a 30um grating texture based on just one to three touches per whisker and can display accurate judgments of a texture within 100 ms of initial whisker contact [2]. In an effort to understand and emulate the whiskered sensing capabilities of rats, many researchers have investigated the use of artificial whiskers for tactile discrimination.

Recent work has explored the capabilities of whiskered sensors from an engineering perspective. Whisker based tactile sensors have the potential to be uniquely useful in a broad range of tasks. As opposed to vision and echo-location, tactile sensation can be performed in complete darkness, in dusty or cloudy environments, and is covert (i.e. does not emit light or sound). Whisker sensors are mechanically very simple, they require very little energy to run, and can work in confined spaces. These properties make whisker sensors ideal for mobile robotics, and would for example be useful when exploring adverse underground environments. Due to their cheapness and simplicity, whiskers could also make effective additions to domestic robots such as vacuum cleaners.

Studies of object location in the whisker field have investigated the use of static beam equations [12], [2], deflection magnitude and time series differences [14]. Hipp et al [11] looked for the features in the whisker signals that allowed the rat to make such fine texture discriminations, and showed that artificial whiskers can be used to discriminate different grades of sandpaper using the power spectral density of the signal.

Navigation, or any high level object recognition task would require some low level feature recognition. In the tactile domain, local texture provides a convenient and robust low-level feature set for building higher level models of object recognition and map building for navigation. For a mobile robot in an office or home environment, floor surface identity provides an ideal cue to location. Recognition of a floor surface as carpet versus vinyl flooring could indicate that the robot is in a living room or kitchen, and boundaries between surfaces within a room are valuable landmarks. For a cleaning robot, floor surface recognition could further activate different cleaning mechanisms, and provide estimates of current odometry noise associated with motion on different surfaces.

Previously we have shown that artificial whiskers can be used for texture discrimination of above-floor objects, by a mobile robot platform making three constrained types of contact with four texturally homogeneous surfaces [9]. If the textured surface's location relative to the platform is known, and the speed of the robot's movement moderated, it is possible to use a range of classifiers to distinguish rough from smooth surfaces. In contrast, the present paper is an 'in the wild' study, with texture data gathered in a real-world office environment.

II. Materials and methods

A. The Whisker

Our whisker sensor consisted of a flexible plastic (Acrylonitrile butadiene styrene (ABS)) whisker shaft (200mm long, 2mm diameter, E $\approx$ 2.3GPa) mounted at its base into a short, polyurethane rubber filled, inflexible tube called a follicle case (see fig 1). ABS plastic was used for the whisker shaft because of its flexibility, appropriate mechanical match to scaled-up biological whiskers, and suitability for rapid prototyping using the Fused Deposition Modeling (FDM) approach. The use of rapid prototyping technology to build the whisker will also contribute significantly to any future investigation into the morphology of the whisker shaft itself.

A magnet was bonded to the base of the whisker shaft in such a way that when the follicle case/whisker shaft assembly was located into the whisker mount (see fig 1), the magnet was positioned directly above a tri-axis Hall effect sensor IC

[1] Active Touch Laboratory, Department of Psychology, University of Sheffield, Western Bank, Sheffield. S10 2TN, UK. *mat.evans@shef.ac.uk*

[2] Bristol Robotics Laboratory, Du Pont Building, Bristol Business Park, Coldharbour Lane, Frenchay, Bristol. BS16 1QD, UK

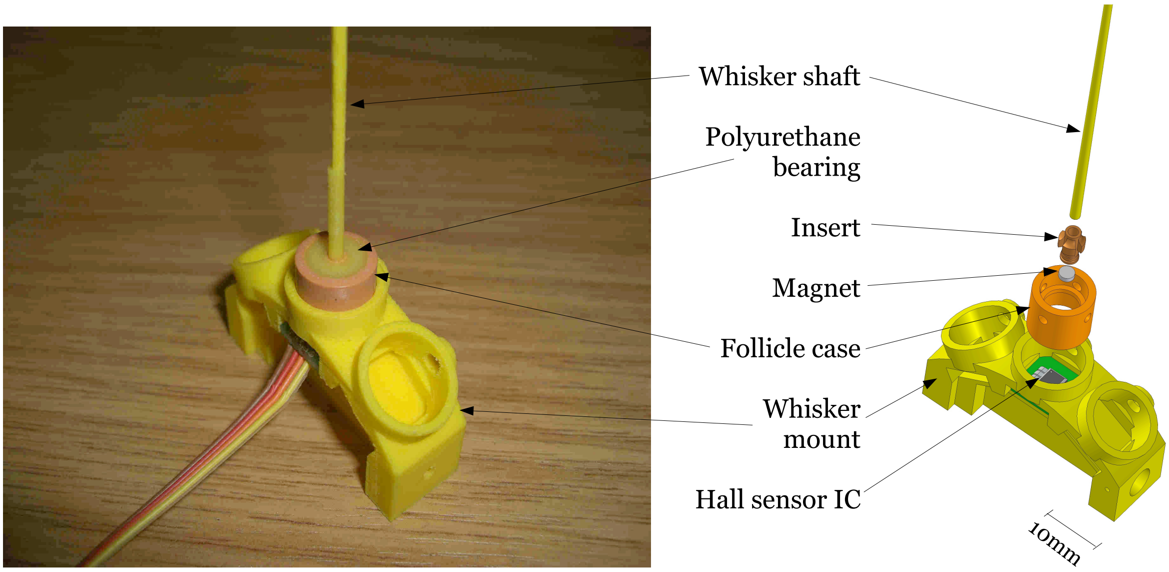


Fig. 1. Diagram of whisker follicle sensor construction

(Melexis MLX90333 [16]). Hall effect sensors measure the change in voltage across a conductor in response to changes in the strength of a nearby magnetic field. The tri-axis Hall effect sensor used here can measure the voltage changes in 3 orthogonal axes, i.e., *x, y, z*. This sensor technology was chosen for its robustness (no physical coupling between sensor and environment), ability to measure displacements in two dimensions, cost ($\approx$ 6 euros), size (S08 IC package 3x4mm) and reprogramability, which allows the sensitivity of the sensor to be adjusted after manufacture to best suit the current experiment or application.

The Hall effect sensor IC was programmed to generate 2 voltages, the magnitudes of which being proportional to the two orthogonal displacement angles (α,β) of the magnet from its resting position above the sensor (see fig 3). As forces are applied to the whisker shaft, the moment experienced at the base will rotate the magnet around the pivot point, nominally in the centre of the polyurethane bearing. A trigonometric operation in the DSP core of the Hall sensor IC decouples the alpha and beta angles and removes the *z*-component introduced by the arc of travel of the magnet, as indicated by the blue dotted line in fig 3. This operation ensures that the output voltages from the IC are linearly proportional to the tangent component of the alpha and beta angles, or *x* and *y* as they will be refered to hereafter.

To set the operating range of the sensor a calibration stand was constructed to allow a fixed deflection, d, to be applied to the whisker shaft at a known radial distance, l, from the base in the 2 dimensions (refer to fig. 3). The output voltage from the IC was then scaled to $\pm d$ in both dimensions, with d=0 set to 50% of the maximum output voltage Vdd, i.e., 2.5V. For the whisker sensor used in the experiments reported here, the voltage range was set as 5 - 95% Vdd through $\pm d$ = 60mm applied at l = 150mm.

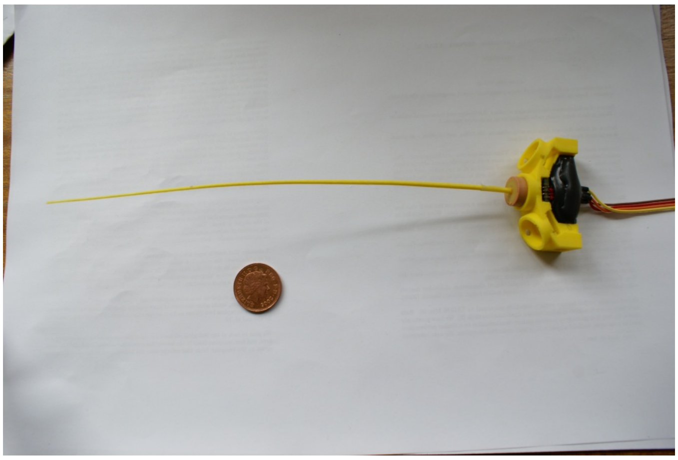


Fig. 2. Artificial whisker shaft and follicle, with a 1p coin for scale

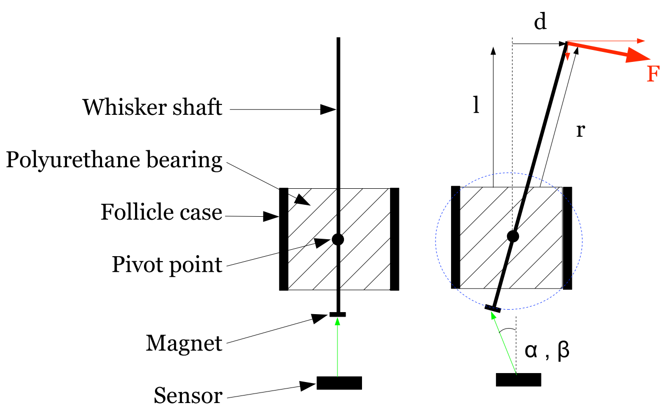
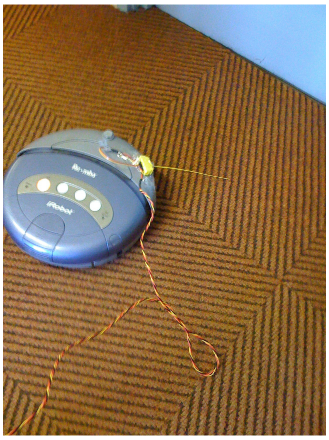


Fig. 3. Diagram of the artificial whisker Hall effect sensor



(a)

(b)

Fig. 4. (a) iRobot Roomba with the artificial whisker sensor attached. (b) A close up of the whisker angled to make contact with the floor

B. The robot

An iRobot Roomba vacuum cleaner (iRobot, 8 Crosby Drive, Bedford, MA 01730) was chosen as the platform for these experiments (fig. 4). This robot was ideal for the task as it would ultimately be the candidate system for any behavioural output from the classification. The Roomba is a commercial robot vacuum cleaner that is programmed to clean carpets autonomously, using three modes chosen by the user, and control is modified by the environment it encounters. A remote control is also provided with the Roomba which allows more direct control over the robot's behaviour. Without access to the preprogrammed algorithms it is difficult to automatically determine the robot's motions during execution of its cleaning modes, so the present work focuses on simple motions produced with the remote control.

The whisker was mounted on the the front of the robot, at 45 degree azimuth from the forwards direction of travel, and a slight downwards elevation sufficient to make constant contact with the floor during movement (see fig. 4). Thus the whisker transduces a constant stream of deflection information as long as the robot is moving.

C. The task

Four surfaces were chosen for classification: two carpets of different roughnesses, a lino surface and a tarmac surface (fig. 5). These surfaces were chosen because they were appropriately generic for a real world experiment, and they provide a range of surface types, while also being sufficiently similar to make classification difficult.

Two primary behavioural conditions were chosen with the robot moving either anticlockwise only, or clockwise only. This provided enough data for developing classifiers for known robot motions. In order to demonstrate the difficulty of classification without knowledge of the robot motion, we also recorded data for each surface during the Roomba's 'spot' cleaning programme. This consists of a series of (externally) unpredictable clockwise, anticlockwise and forward motions.

As the robot moved the whiskers were swept across the floor. Any deflections of the whisker were transmitted through the hall effect sensors through a LabJack UE9 USB data acquisition card (www.labjack.com) at a rate of 2 kHz for each of the x and y directions. This data was sent to a computer through the BRAHMS middleware (brahms.sourceforge.net) for analysis in MATLAB (www.mathworks.com). Example data from the four floor surfaces is shown in fig. 6.

III. Results

A. The data

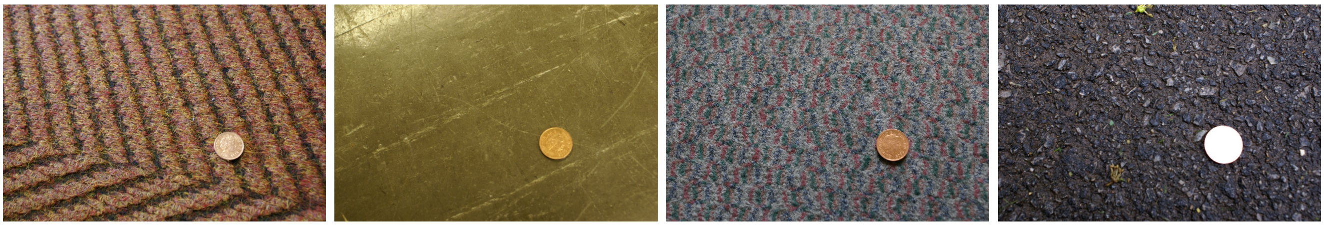
For each behavioural condition the Labjack sampled data while the robot moved in a specific direction for 16 seconds. Each 16-second trial was then repeated 4 times for each of the behavioural conditions, and 4 times for the spot command. Data from the Labjack is passed to the computer in packets of 160 recordings each (at 2kHz. 0.08s, or 200 packets per 16 second trial) to ensure seamless acquisition of the data with no bottleneck at the Labjack. When the data is sampled there is no guarantee that the robot will be moving, so to aid the classification the packets acquired when the robot was stationary were removed. A MATLAB script was written to remove any packets where the variance in the signal was below 5×10^{-5}. This automated process provided a clean signal for classification. The remaining packets were restructured to windows for classification that were 800 recordings long (0.4s, or 40 per 16 second trial). These restructured windows were then separated evenly into training and test data sets by assigning all odd numbered samples to the training set, and all even numbered samples to the test set. Only the training set was then used to develop any classifiers. Classifiers were then applied to the test set, and their performance measured using confusion matrices.

B. Analysis

Classification was performed using a template based classifier on the fast fourier transfer (FFT) of the windows. The FFT was carried out on each window in the training dataset. The absolute values of each squared FFT'd signal were taken and the first value was set to zero to remove the mean signal component. The spectra were then smoothed by convolving with a 10-point uniform window, then L1-normalized. Templates were generated by averaging all FFT'd windows in the training set for each surface (rough and smooth carpet, vinyl and tarmac) and behavioral condition (clockwise, anticlockwise and spot). Templates from the clockwise condition are shown in fig. 7. The templates were compared to the FFT of each window in the test data set in turn using a sum of squared errors over the spectra, and hard classification was made by selecting the template with the lowest error.

C. What we found

Table (I) and (II) show confusion matrices for four-way texture discrimination in the anti-clockwise and clockwise movement conditions respectively. Though mean classification performance is good in both movement



(a) Rough carpet (b) Vinyl Flooring (c) Smooth Carpet (d) Tarmac

Fig. 5. Photos of all the surfaces, with 1p coins for scale.

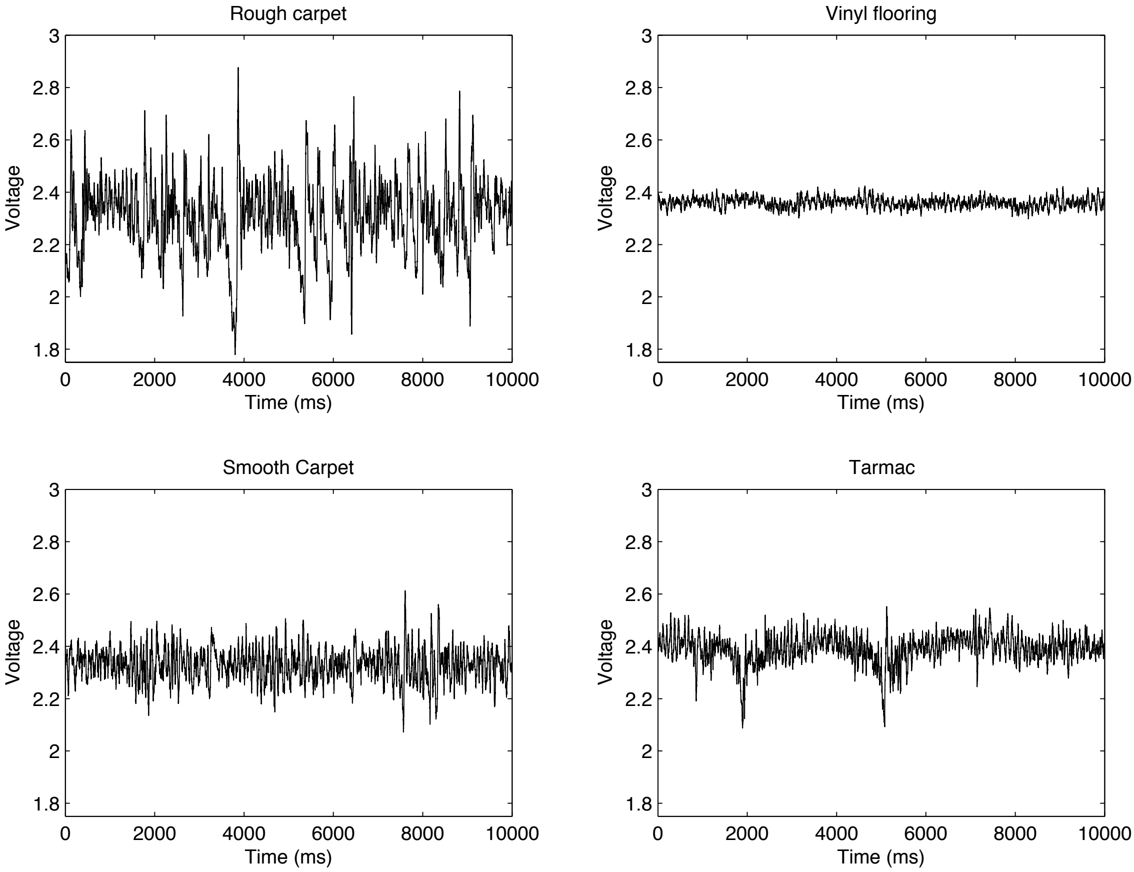


Fig. 6. Example signals from the artificial whisker sampled from the four floor surfaces.

conditions, there is quite a significant difference in performance between the conditions. Overall, classification in the anti-clockwise movement condition is better (Mean correct = 72%, vs 64%), though classification of the vinyl flooring is more accurate in the clockwise condition (79% vs 68% correct). Smooth carpet classification is extremely poor in the clockwise movement condition (33% correct), as can be seen in the third column of table (II).

Table (III) shows the performance of the classifier in the spot program movement condition. Though overall performance is poorer in this condition than the previous single direction of movement tests, it is still well above chance. Also, the confusion matrix clearly shows that performance overall is very good in three of the four conditions, with misclassification of smooth carpet (11% correct) accounting for the low mean correct score.

In a further analysis, we tried classifying each behavioural condition with the templates from the other, clockwise templates on the anti-clockwise data and vice versa, to see how robust these templates were. The performance in this test was much poorer, with the mean correct scores on both datasets falling to 52%.

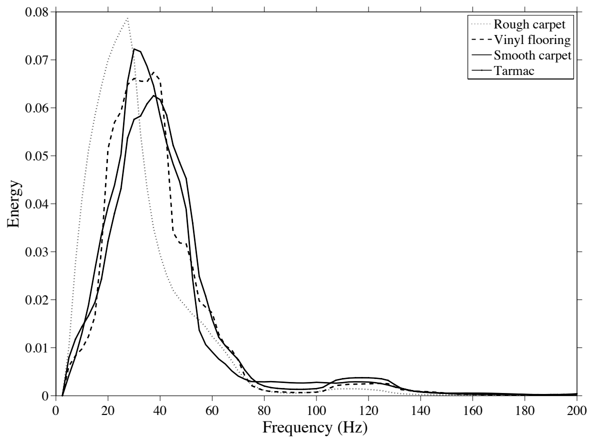


Fig. 7. Templates used for surface classification in the clockwise movement condition

TABLE I

CONFUSION MATRIX FOR CLASSIFICATION IN THE ANTI-CLOCKWISE DIRECTION OF MOVEMENT CONDITION. MEAN CORRECT = 72%

AC	Rough carpet	Vinyl	Smooth carpet	Tarmac
Rough carpet	78	6	12	10
Vinyl	1	54	4	12
Smooth carpet	0	1	43	4
Tarmac	1	19	21	54
Correct %	97.5%	67.5%	54%	67.5%

TABLE II

CONFUSION MATRIX FOR CLASSIFICATION IN THE CLOCKWISE DIRECTION OF MOVEMENT CONDITION. MEAN CORRECT = 64%

C	Rough carpet	Vinyl	Smooth carpet	Tarmac
Rough carpet	64	6	26	11
Vinyl	0	63	0	9
Smooth carpet	11	1	27	8
Tarmac	5	10	27	52
Correct %	80%	79%	33%	65%

TABLE III

CONFUSION MATRIX FOR CLASSIFICATION IN THE 'SPOT' MOVEMENT CONDITION. MEAN CORRECT = 56%

Spot	Rough carpet	Vinyl	Smooth carpet	Tarmac
Rough carpet	60	7	48	7
Vinyl	0	48	1	2
Smooth carpet	13	3	9	9
Tarmac	7	22	22	62
Correct %	75%	60%	11%	77.5%

IV. DISCUSSION

These results show that the performance of these classifiers are dependent on the movement of the robot. Though classification performance is good on most surfaces across all conditions, movement would need to be taken into account for classification of all surfaces to be optimised. There are two reasons for this discrepancy in classification for different movement conditions. Firstly, as can be seen in fig. 4, the whisker was not mounted precisely perpendicular to the outer case of the Roomba, so movement in one direction or another would deflect the whisker differently. For example by moving in an anticlockwise direction the whisker tip is dragged behind the rest of the shaft, whereas clockwise movement forces the tip forwards slightly into the ground. These two different contact patterns could affect the signals coming from the whiskers, by either magnifying or suppressing small bumps in the surface. Secondly the movement of the robot itself was quite different in the two conditions, with anti-clockwise movement being combined with a slight forward movement to produce a smooth spiraling motion. On the other hand clockwise motion was a pure rotation, and as a result the motion of the robot was much less smooth. Without taking the robot apart, or knowing what the Roomba's operating system actually commands, we cannot know the reasons for these differences exactly. We can suggest that the spiraling anti-clockwise movement combined with a rotational clockwise avoidance movement would provide enough flexibility for efficient cleaning while keeping the movement choices at any one time low. This would be desirable for a robot with the Roomba's operational goal to work robustly and efficiently.

What is clear is that for texture discrimination in a mobile robot the movement of the system, and as a result the trajectory and geometry of the whisker contact with the surface, would need to be known before an accurate decision can be made about the surface. Given that any robot movement would be controlled by the same system that is hoping to process the whisker information this motor-efference signal would be available, making deciphering the signals easier. Robot movement could be controlled to accentuate certain aspects of the signal, in this case by turning in the most discriminating direction. For example, if a general 'rough' category decision has been made, the robot could then move in a way that provides the most accurate 'rough carpet'/ 'tarmac' discrimination. Following on from our findings here, the robot could always move clockwise upon start-up to accurately check if the surface is vinyl flooring, then move anti-clockwise to better discriminate the three other surfaces. In this way, all of the robot's movements could be optimised for a given task, and decisions will be as quick and accurate as possible.

Additional, biologically inspired, methods could be implemented in future to highlight any differences between very similar textures. Arabzadeh et al [6] showed that the pattern of spikes in the primary afferents provide more information about the texture encountered by the whisker than spike number alone. They suggest that the pattern of spikes in the trigeminal ganglion and cortex are representing the temporal pattern of deflections at the whisker tip. Others have proposed that the rats may sweep their whiskers along textured surfaces in such a way as to amplify the frequency of the texture by monitoring the resonance of the different whiskers [18], [19]. Rats adjust the movement of their whiskers to extract the most information possible from the surface by ensuring frequent and numerous light touches [17], and by controlling the speed and spread of the whiskers before initial contact and between multiple contacts [10]. Whisking speed would affect the fundamental frequency of the whisker deflections in the signal much like a record being played at the wrong speed, with higher or lower speed causing frequencies to increase or decrease, respectively.

V. Concluding remarks and future work

Simple real-world floor texture classification is possible and could for example be used to adjust the Roomba's mechanical cleaning mode for different surfaces. A more general application of texture classification is as an observation category for probabilistic navigation models (e.g. [22]). In navigation, the task is to infer the current location from noisy observations and odometry. Knowing the surface type allows estimation of the noise in the odometry and allows more accurate fusion with sensor data. For tactile-only robots, such as those operating covertly in hostile environments, regions of texture and boundaries between them could form useful observations to provide location likelihoods.

Template based classification is a discriminative method, and its success suggests that whisker signals could provide immediate information about the surfaces in the world with minimal processing. This is in contrast to generative modelling which needs to consider all possible candidate causes of the signal and search for the best top-down explanation. As they work for artificial whiskers, discriminative methods might also be found in low-level biological whisker sensory-motor loops for prey capture or avoidance, having less latency than hierarchical cortical processing.

In previous work using constrained contacts with *above*-floor objects [9] we showed that the accuracy of several texture discriminators is greatly improved when given knowledge of the geometry of the contact. (This is not an issue with floor surfaces, which are constantly in contact with the whisker.) We have shown in simulation [8] that larger-scale templates can be used to estimate the contact geometry with above-floor objects (alternatively, generative beam-theoretic methods also exist for such estimation [2]). Future work will explore how to fuse such geometric knowledge with texture classifiers to improve the accuracy in real-world, mobile, above-floor texture discrimination.

VI. Acknowledgements

The authors would like to thank members of the Active Touch Laboratory at Sheffield (ATL@S) and the Adaptive Behaviour Research Group (ABRG) for their suggestions, knowledge and patience.

This work was supported by the EPSRC Doctoral Training Scheme and EU grants ICEA (IST-027819) and BIOTACT (ICT-215910).

References

[1] Ehud Ahissar and David Kleinfeld. Closed-loop neuronal computations: focus on vibrissa somatosensation in rat. *Cereb Cortex*, 13(1):53–62, 2003.

[2] J Alexander Birdwell, Joseph H Solomon, Montakan Thajchayapong, Michael A Taylor, Matthew Cheely, R Blythe Towal, Jorg Conradt, and Mitra J Z Hartmann. Biomechanical models for radial distance determination by the rat vibrissal system. *J Neurophysiol*, 98(4):2439–2455, 2007.

[3] G E Carvell and D J Simons. Biometric analyses of vibrissal tactile discrimination in the rat. *J Neurosci*, 10(8):2638–2648, 1990.

[4] Mathew E Diamond, Moritz von Heimendahl, and Ehsan Arabzadeh. Whisker-mediated texture discrimination. *PLoS Biol*, 6(8):e220, 2008 Aug 26.

[5] Mathew E Diamond, Moritz von Heimendahl, Per Magne Knutsen, David Kleinfeld, and Ehud Ahissar. 'where' and 'what' in the whisker sensorimotor system. *Nat Rev Neurosci*, 9(8):601–612, 2008 Aug.

[6] Stefano Panzeri Ehsan Arabzadeh and Mathew E. Diamond. Deciphering the spike train of a sensory neuron: Counts and temporal patterns in the rat whisker pathway. *The Journal of Neuroscience*, 26(36):9216–9226, 2006.

[7] Daniel E Feldman and Michael Brecht. Map plasticity in somatosensory cortex. *Science*, 310(5749):810–815, 2005.

[8] Charles W Fox, Mat Evans, Martin Pearson, and Tony J Prescott. Towards temporal inference for shape recognition from whiskers. In Subramanian Ramamoorthy and Gillian M. Hayes, editors, *Towards Autonomous Robotic Systems*, pages 226 – 233, 2008.

[9] Charles W Fox, Ben Mitchinson, Martin Pearson, Anthony G Pipe, and Tony J Prescott. Contact type dependency of texture classification in a whiskered mobile robot. *Autonomous Robots*, 2009.

[10] Robyn A. Grant, Ben Mitchinson, Charles W. Fox, and Tony J. Prescott. Active touch sensing in the rat: Anticipatory and regulatory control of whisker movements during surface exploration. *Journal of Neurophysiology*, 101:862–874, 2009.

[11] Joerg Hipp, Ehsan Arabzadeh, Erik Zorzin, Jorg Conradt, Christoph Kayser, Mathew E Diamond, and Peter Konig. Texture signals in whisker vibrations. *J Neurophysiol*, 95(3):1792–1799, 2006.

[12] Makoto Kaneko. Active antenna. *Robotics and Automation, IEEE Transactions on*, pages 2665–2671, 1994.

[13] DaeEun Kim and Ralf Moller. A biomimetic whisker for texture discrimination and distance estimation. In S. Schaal et al, editor, *From Animals to Animats 8, Proceedings of the International Conference on the Simulation of Adaptive Behaviour*, pages 140–149. MIT Press, 2004.

[14] DaeEun Kim and Ralf Moller. Biomimetic whiskers for shape recognition. *Robotics and Autonomous Systems*, 55:229–243, 2007.

[15] David Kleinfeld, Ehud Ahissar, and Mathew E Diamond. Active sensation: insights from the rodent vibrissa sensorimotor system. *Curr Opin Neurobiol*, 16(4):435–444, 2006.

[16] Melexis. *www.melexis.com/assets/mlx*90333*_datasheet_*5276*.aspx*.

[17] Ben Mitchinson, Chris J Martin, Robyn A Grant, and Tony J Prescott. Feedback control in active sensing: rat exploratory whisking is modulated by environmental contact. *Proc Biol Sci*, 274(1613):1035–1041, 2007.

[18] Maria A Neimark, Mark L Andermann, John J Hopfield, and Christopher I Moore. Vibrissa resonance as a transduction mechanism for tactile encoding. *J Neurosci*, 23(16):6499–6509, 2003.

[19] Jason. Ritt, Mark L. Andermann, and Christopher Ir. Moore. Embodied information processing: Vibrissa mechanics and texture features shape micromotions in actively sensing rats. *Neuron*, 57:599–613, February 2008.

[20] Marcin Szwed, Knarik Bagdasarian, and Ehud Ahissar. Encoding of vibrissal active touch. *Neuron*, 40(3):621–630, 2003.

[21] Marcin Szwed, Knarik Bagdasarian, Barak Blumenfeld, Omri Barak, Dori Derdikman, and Ehud Ahissar. Responses of trigeminal ganglion neurons to the radial distance of contact during active vibrissal touch. *J Neurophysiol*, 95(2):791–802, 2006.

[22] Sebastian Thrun. Probabilistic robotics. *Communications of the ACM*, 45(3):52–57, March 2002.