Tactile discrimination using template classifiers: Towards a model of feature extraction in mammalian vibrissal systems

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Abstract. Rats and other whiskered mammals are capable of making sophisticated sensory discriminations using tactile signals from their facial whiskers (vibrissae). As part of a programme of work to develop biomimetic technologies for vibrissal sensing, including whiskered robots, we are devising algorithms for the fast extraction of object parameters from whisker deflection data. Previous work has demonstrated that radial distance to contact can be estimated from forces measured at the base of the whisker shaft. We show that in the case of a moving object contacting a whisker, the measured force can be ambiguous in distinguishing a nearby object moving slowly from a more distant object moving rapidly. This ambiguity can be resolved by simultaneously extracting object position and speed from the whisker deflection time series – that is by attending to the dynamics of the whisker's interaction with the object. We compare a simple classifier with an adaptive EM (Expectation Maximisation) classifier. Both systems are effective at simultaneously extracting the two parameters, the EM-classifier showing similar performance to a handpicked template classifier. We propose that adaptive classification algorithms can provide insights into the types of computations performed in the rat vibrissal system when the animal is faced with a discrimination task.

Introduction

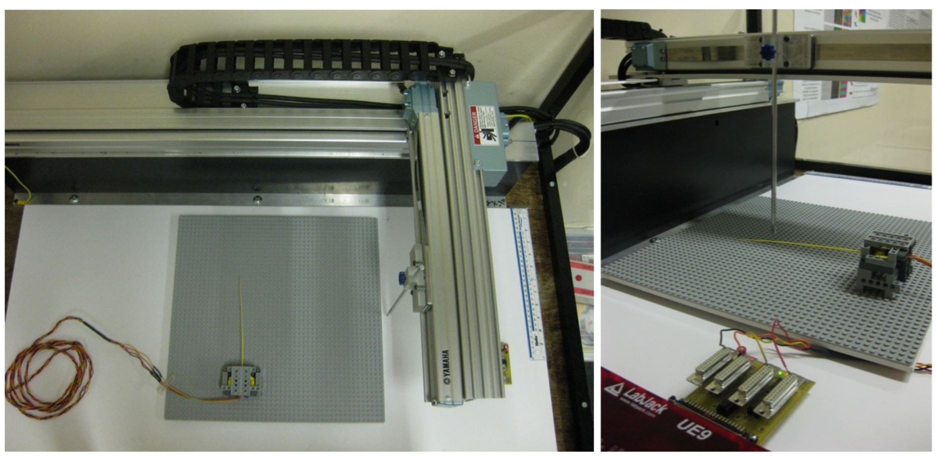
Rats, mice and other whiskered mammals can discriminate a variety of tactile object properties using only their facial whiskers (vibrissae). For instance, rats are able to discriminate surface textures, with different degrees of roughness, with similar acuity to the human fingertip [4]; the Etruscan shrew - the smallest living mammal - can recognise and localise prey animals (insects) from a small number of fleeting whisker contacts, sufficient to allow fast and precisely targeted attacks [1]; and sea mammals such as seals and walruses are able to make judgements about object size, shape, and direction of movement, using only tactile signals from their vibrissae [5].

Several properties of the vibrissal system make it stand out as an interesting model system in which to investigate theories about the sensory guidance of behaviour. First, in tactile sensing systems generally, the sensory apparatus is usually brought into contact with objects in a deliberate and controlled manner. Whether it is a person exploring an object contour with their fingertips or a rat palpating (whisking) its vibrissae against a surface, purposive control or active sensing is key to information acquisition [14]. Second, the processing of tactile signals may require a relatively small number of stages. For instance, in the rat, there are multiple closed loops connecting vibrissal signals to actuation mechanisms such that new information can begin to influence behaviour after passing through just a small number of synapses [12]. Processing can also be very fast. For instance, whisker contact signals can reach the barrel cortex – from where they can begin to effect processing in behaviour-related areas such as the motor cortex, the superior colliculus, and cerebellum – in just 7 milliseconds [7]. The rat brain thus appears to be tuned to pick out the behaviourally-relevant aspects of vibrissal signals rapidly and in just a small number of steps.

Inspired by the vibrissal systems of mammals, we are working to develop artificial whisker systems for fast and accurate tactile discrimination – which could be useful for mobile robots – and at the same time can be used to test theories of mammalian sensorimotor control. Previous work has shown that information about texture, distance to contact, and shape can be extracted from signals obtained when an artificial whisker is moved against a surface [9] [8] [11] [6]. Our current work extends these findings in several directions. First, by exploring how classifier systems can be trained to extract a range of different tactile properties from whiskers signals with relatively little preprocessing of the sensor input. Second, by showing that such systems can extract multiple features simultaneously from the same signal. Third, by investigating the effects of active control of the sensor apparatus on the problem of tactile feature discrimination. At the same time, though described elsewhere, we are developing decision-making algorithms for these systems that can optimise the speed-accuracy tradeoff [13].

Developing models of whisker based perception has been problematic. In passive sensory modalities such as vision and audition it is generally quite easy to present stimuli to a passive sensor on a robot, or images and tones can be simulated and used to train a computational model. There is no obvious analog for tactile stimuli, and the true nature of tactile stimuli is too poorly understood to be simulated accurately. Whiskers are especially difficult to simulate accurately, as they have very low mass but high spring constants when modelled as a series of masses on rotational springs, leading to numerical instabilities. Additionally when the parameters of a whisker-object contact become more numerous (e.g. speed and radial distance to contact, surface texture, orientation and softness etc) it becomes very difficult to constrain the contact and generate reliable signals in either simulated or physical robots. For these reasons acquiring sufficient examples of carefully controlled whisker contacts with tactile stimuli to train models and classifiers has proved difficult. To facilitate the study of artificial vibrissal sensing we therefore present here a novel system for generating large sets of tactile stimuli and deflection signals. An XY positioning robot is programmed to move objects into an artificial whisker sensor in an accurate and highly repeatable manner (Fig.1). Deflections for the whisker are streamed to a PC, and can be processed in real time to control subsequent movement of the robot arm. Under passive deflections the object moved by the robot arm makes contact with the artificial whisker and deflects the whisker through a large angle. When deflection reaches a critical point the whisker loses friction with the object, deforms and deflects past the object and goes through oscillatory ringing until the energy dissipates and the whisker comes to rest. However, in addition to passive touch experiments we are also able to use our experimental setup to investigate active sensing. In this case we mimic a control policy that we have observed in rats in our own laboratory whereby the protraction of a whisker ceases rapidly on contact with a surface and whisker then begins to retract [14]. In contrast to the passive case, this policy, which we call Minimal Impingement (MI), keeps the amplitude and duration of whisker deflection within a limited range, and also keeps whisker ringing after contact to a minimum. An additional benefit is that the forces acting on the whisker are much smaller, meaning whisker breakage is less likely – an important consideration for autonomous robotics.

The remainder of this paper motivates and describes a discrimination algorithm developed using this test-bed and shows its utility under differing parameters for accurately extracting object features from vibrissal deflection signals. In future work these algorithms will be transferred to operate in less constrained circumstances onboard mobile robot platforms such the SCRATCHbot robot described in our partner paper [15].



(a) (b)

Fig. 1. The XY positioning robot (a) from above, to show the range of movement available. (b) From the side

Simultaneous radial distance and speed task

The object properties we chose to manipulate and attempt to recognize were radial distance to contact from the base, and contact speed. The task is to recognise these two parameters *simultaneously*. To investigate this problem we presented a vertical pole to the whisker at a range of radial distances from the base, and at different movement speeds. We show that, depending on the features used for classification, radial distance detection is confounded with contact speed. Previous work [3] [10] has shown that a rat could encode the radial distance to contact along a whisker by monitoring the magnitude of forces (or moments) at the base. Others have suggested that the increased firing rate of cells in the whisker sensory nerve, for contacts close to the base, could be due to the increased moments at the whisker base. Static beam equations, and analyses relying on instantaneous measures of moments do not account for the dynamic properties of objects. If an object collides with a whisker at the same location but at different speeds it will induce different forces at the base. For example, under the right conditions the moment at the base will be the same for a slowly moving object contacting near the base, and a fast object near the tip (see Fig.2 for a demonstration of this). This ambiguity in the signal cannot be accounted for with a single observation, an additional observation or feature must be found in order to discriminate these two properties of the collision. Successful classification relies either on finding the contact speed before conducting a radial distance estimation, or discriminating both properties simultaneously. In the analysis we assess a simple template-based classifier and compare its performance to a classification using an adaptive template classifier, or EM (Expectation Maximisation) algorithm [2] based classifier. Previously we have shown that templates can be used for discriminating tactile features in simulation [8], and that spectral templates can be used to discriminate whisker deflection signals from floor surface textures in a real world environment [6]. In these cases the templates were hand-picked from the data set for better classification. In the present study we show that template based classification can be used to successfully discriminate ambiguous whisker signals in hardware, and that the templates can be found adaptively using a simple Hebb-like learning algorithm.

Methods

The XY positioning robot. An XY positioning robot (Yamaha-PXYX, Yamaha Robotics) (see Fig.1) was used to move objects into the whisker. The robot has a movement range of 350x650mm, and can move up to 720mm/s. Repeatability of the robot is $\pm$0.01mm, and the maximum load it can carry is 1.5kg. Objects are carried by the robot into an artificial whisker fixed to the table, as this allows us to control the contact as carefully as possible. Moving the whisker into an object would cause the whisker to oscillate unpredictably during movement between contacts, and as a result each contact would be slightly different. A controller (Yamaha RCX 222, 2-axis robot controller) takes instructions from a PC through an RS232 cable, and the controller interprets the instructions, completes path integration, and drives the motors. Instructions for the robot are generated inside a Matlab (www.mathworks.com) loop, and can be easily updated during robot operation, depending on the whisker input.
The Whisker. A whisker sensor was taken from the SCRATCHbot robot platform (described in detail in [15] [16]). Technical details of the whisker can be found in [6]. A tapered, flexible plastic whisker, $\approx$5 times scale models of a rat whisker, was mounted into an inflexible rubber-filled 'follicle' case (Fig.3(a)). A tri-axis hall effect sensor mounted in the follicle case measures the deflection of a magnet fixed to the base of the whisker shaft (Fig.3(b). The hall effect sensor IC was programmed to generate two volt-

ages, corresponding to the magnitude of the whisker base deflection in two directions, *x* and *y*.

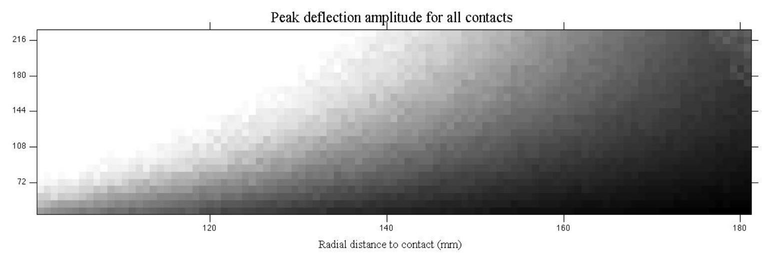
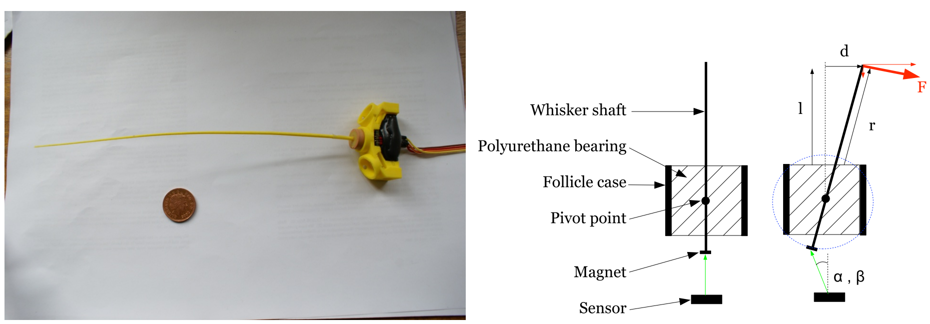


Fig. 2. Peak deflection magnitude for each speed-radial distance pair. Deflection magnitude (brightness of pixel), or force, has been used in the past as a discriminator of radial distance to contact. Here a given radial distance results in differing deflection magnitudes depending on movement speed. If deflection magnitude were a sufficient criteria for radial distance estimation, the brightness would decrease evenly across all speeds (Y axis).



(a) (b)

Fig. 3. Artificial whisker shaft and follicle, with a UK 1 pence coin for scale (b)Diagram of the artificial whisker Hall effect sensor.

Data. Deflections of the whisker were transmitted through the hall effect sensors to a LabJack UE9 USB data acquisition card (www.labjack.com) at a rate of 1 kHz for each of the *x* and *y* directions. Each trial lasted 4s. This data was sent to a computer through the BRAHMS middle- ware (brahms.sourceforge.net) for analysis in Matlab.

Robot control. Minimal impingement was implemented by instructing the robot to move an object into the whisker at a given speed until a deflection threshold is crossed, at which point the robot retracts the object as fast as possible (720mm/s). Temporal latency for the loop is $\approx$ 300ms from initial contact due to the controller duty cycle. Though this latency is short enough for the present study, we are working to reduce this latency by gaining more direct control over the robot motors.
The task. Preliminary investigations highlighted that the closest contact that could be made by the whisker at any reasonable speed without saturating the Hall effect sensor was $\approx$80mm from the base. Contacts at less than 5mm from the tip did not deflect the base of the whisker for long enough before slipping past to allow an MI type contact. Therefore, the 185mm length whiskers provide a 100mm range of radial distances. Contact speeds above 216mm/s either cause the whisker to slip past the object before a retraction, or saturates the sensors. 36mm/s was the lower bound on the speed here. Contacts were sampled at radial distance intervals of 1mm, and speed intervals of $\approx$7mm/s over the previously described ranges. In total 101 radial distances and 26 speeds were sampled, giving 2626 different radial distance and speed combinations. Contact combinations were randomly interleaved to limit any affects of changing whisker properties. For each contact combination the whisker was deflected by the robot in both a clockwise and anticlockwise directions (-ve and +ve in x), ensuring that the whisker did not bend over time through repeated unilateral deflections. The experiment was performed twice to generate sufficient data for classification.

Data from each trial was stored separately. Deflections from the clockwise robot movement trials (-ve in x) were converted so all data samples were equivalent. Trials were ordered into arrays by speed and radial distance to contact. Each trial was aligned to peak deflection, and shortened to only the 325ms either side of the peak deflection (751 data samples in total).

Analysis

The data were separated into training and test sets that were each complete data sets of 26 speeds and 101 radial distances. Signals were placed in the training or test sets at random from the original data. In each case classifiers were developed on the training sets, and performance was determined on the test set.
Template based classification. Template based classification involves recording example sensory data as templates during a training phase, and comparing the stored templates to novel data during the test phase. By systematically comparing the novel data to signals encountered previously, a classification can be made by declaring which of the stored templates the novel signal is most similar to. In the present study each template corresponds to a speed-radial distance pair. Classification based on these templates is therefore simultaneous classification of both speed and radial distance. From the training data set a subset of trials – representative of the larger set – were stored in an array as templates. The number of templates chosen were dependent on the experimental condition. During the test phase, trials were taken at random from the test set as inputs to the classifier. An element-wise sum of squared errors calculation was made between the input I and each template T_i,

$$e(T_i) = \sum_{t=1}^{n} (I(t) - T_i(t))^2. \quad (1)$$

where n is the length of the template, in samples. The template with the lowest sum of squared error was determined the winner, and a recording was made in an output array of the estimated speed and radial distance to contact of the input trial. We conducted the experiment with a full complement of templates (26x101) as a benchmark for classification, as well as with two reduced sets of templates, (13x50 and 7x26 templates respectively).

Adaptive EM template based classifier. Picking templates by hand, though successful, is an inefficient method of developing a classifier. A better method is to adaptively learn a set of templates in an unsupervised way, to find a set that covers the bulk of the data space for a given number of templates. Such adaptation can be performed with an EM algorithm [2]. Each time a classification is made it is verified against the true value of the two contact parameters. If the classification was correct, the winning template is modified to be more like the input pattern. If the classification was incorrect, the appropriate losing template is modified to be more like the input pattern. This template modification is achieved by taking a weighted mean of the template and the input,

$$T = \frac{(I + \alpha T)}{1 + \alpha} \quad (2)$$

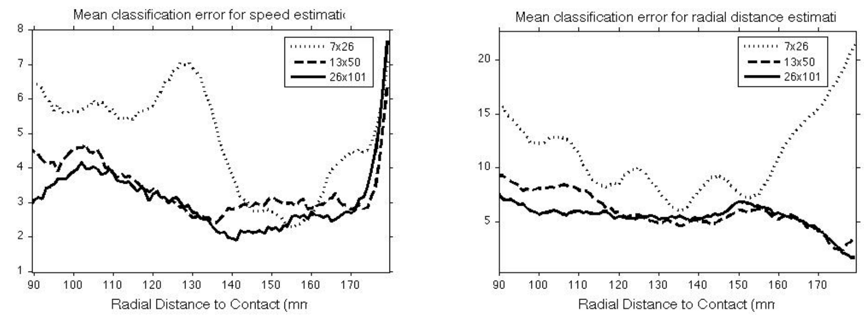
where α is the learning rate of the classifier. By increasing $alpha$ it is possible to learn quicker, but it is less likely that an optimal value will be reached. (The positive and negative modifications to templates may be viewed as Hebbian and anti-Hebbian learning respectively, for templates as linear neurons.) We decided to run the adaptive classifier with a reduced set of templates (13x50), to see if it was possible to achieve performance close to or equivalent to that of hand picked templates.

Results

Template based classifier. The template based classifier with 13x50 templates was capable of successfully classifying 65% of inputs to within 50mm/s of speed and 10mm of radial distance. This performance decreases as the number of templates used is reduced.

Adaptive EM template classifier. We found that after training the Adaptive EM template classifier was capable of classifying 66% of inputs to within 50mm/s of speed and 10mm of radial distance.

Fig.5 shows the results in graphical format. Input signals are shown, arranged for speed and radial distance. Pixel brightness indicates the value assigned to that input signal. A completely correct classification of speed (Fig.5(a) would appear as a gradual transition from dark to light vertically along the Y axis, and a corresponding transition from light to dark horizontally along the X axis for correct radial distance detection (Fig.5b). We can see that both classifiers achieve some degree of correct classification, as well as a number of mistakes. Classification tends to be best for larger radial distances (contacts nearer the tip, lower right region of each plot). Contacts at high speed and near the base tend to be systematically misclassified (upper left region of each plot). Fig.4 shows the mean error of classification for each point along the whisker. Error is lowest in the region near, though not at, the whisker tip. Performance of the classifiers with reduced sets of templates is good, though the performance of the classifier with the fewest (7x25) templates is less reliable over certain regions of the space.

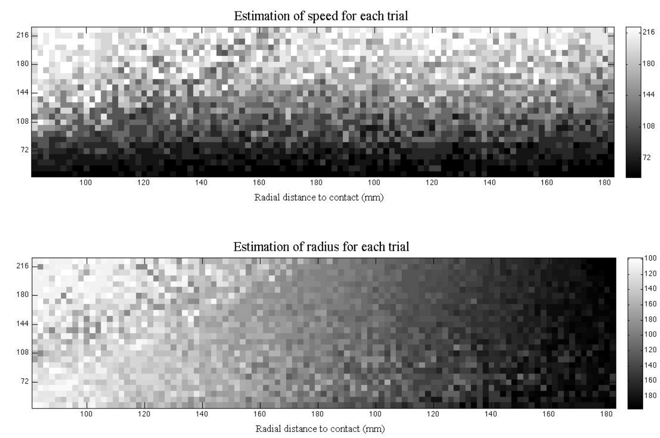


(a) (b)

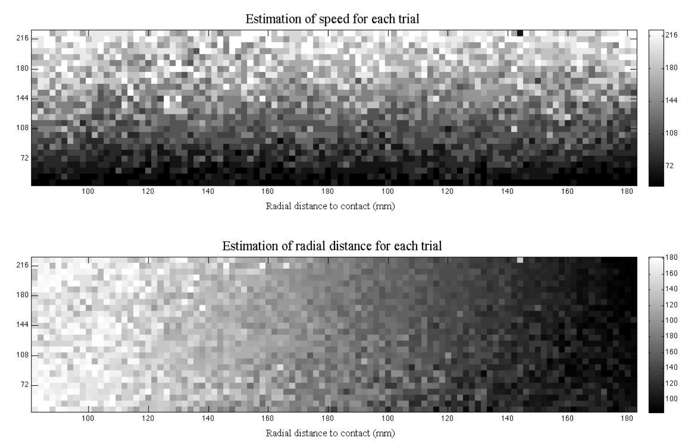
Fig. 4. Mean classification error for each radial distance along the whisker, for different numbers of templates. Y axis corresponds to mean distance between the real and predicted values of speed (a) and radial distance (b). Error is at its lowest in the portion of the whisker near, though not at, the tip.

Discussion

By collecting a large data set and exhaustively tiling a feature space we have shown that certain features in the whisker signal that are ambiguous in isolation can be simultaneously discriminated using a robust, and computationally cheap adaptive classified system. Previously we have shown [9][6] that successful classification of surface properties, such as texture, is highly dependent on knowing the location of the surface and the nature of the contact. We believe that the first steps towards the goal of simultaneously extracting a range of relevant object properties have now been taken. The success of the classifiers at contacts nearer the tip may also go some way to explain the whisking behaviour seen in rats. Rats appear to control their whiskers so as to make contacts at or near the whisker tip [14], possibly because this creates signals that vary more predictably across contact parameters allowing the animal to make better judgements. More generally, keeping whisker deflection amplitude and duration within a limited range using active sensing strategies will allow the development of classifiers that are more sensitive to smaller changes in the input. Indeed, the data presented here suggests that contacts of this type are easier to discriminate over a particular section of the whisker, suggesting a ’sweet spot’ of whisk speed and whisker contact location. The development of fast, adaptive classifiers for tactile feature discrimination could also provide insights into signal processing in areas of the vibrissal system such as the barrel cortex where the rat is known to be able to rapidly extract behaviourally-relevant properties of the stimulus in a small number of processing stages. Ullman et al [17] have proposed that the visual system operates through hierarchies of progressively more complex adaptive feature-matching templates. The ideas investigated in the current paper might therefore be considered as the first step towards identifying a similar, general scheme for understanding cortical processing in the domain of touch.



(a)



(b)

Fig. 5. Classification performance of the EM template classifier (a), against that of a classifier with hand picked templates.

References

1. Farzana Anjum, Hendrik Turni, Paul G H Mulder, Johannes van der Burg, and Michael Brecht. Tactile guidance of prey capture in etruscan shrews. *Proc Natl Acad Sci U S A*, 103(44):16544–16549, 2006.
2. A.P.Dempster, N.M. Laird, and D.B. Rubin. Maximum likelihood from incomplete data via the em algorithm. *Journal of the Royal Statistical Society. Series B (Methodological)*, 39(1):1–38, 1977.
3. 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.
4. G E Carvell and D J Simons. Biometric analyses of vibrissal tactile discrimination in the rat. *J Neurosci*, 10(8):2638–2648, 1990.
5. G. Dehnhardt and G. Ducker. Tactual discrimination of size and shape by a california sea lion (zalophus californianus). *Animal Learning and Behavior*, 24(4):366–374, 1996.
6. Mat Evans, Charles W Fox, Martin J. Pearson, and Tony J Prescott. Spectral template based classification of robotic whisker sensor signals in a floor texture discrimination task. In T Kyriacou, U. Nehmzow, C. Melhuish, and M. Witkowski, editors, *Proceedings of Towards Autonomous Robotic Systems (TAROS 2009)*, pages 19–24, 2009.
7. Isabelle Ferezou, Sonia Bolea, and Carl C H Petersen. Visualizing the cortical representation of whisker touch: voltage-sensitive dye imaging in freely moving mice. *Neuron*, 50(4):617–629, 2006.
8. Charles 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 J Pearson, Anthony G Pipe, and Tony J Prescott. Contact type dependency of texture classification in a whiskered mobile robot. *Autonomous Robots*, 2009.
10. M. Kaneko, N. Kanayama, and T Tsuji. Active antenna for contact sensing. *Robotics and Automation, IEEE Transactions on*, 14(2):278–291, Apr 1998.
11. DaeEun Kim and Ralf Moller. Biomimetic whiskers for shape recognition. *Robotics and Autonomous Systems*, 55:229–243, 2007.
12. 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.
13. N. F. Lepora, M. Evans, C. W. Fox, M. E. Diamond, K. Gurney, and T. J. Prescott. (submitted) naive bayes texture classification applied to whisker data from a moving robot. In *World Congress on Computational Intelligence.*, 2010.
14. 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.
15. Martin J. Pearson, Ben Mitchinson, Jason Welsby, Tony G Pipe, and Tony J. Prescott. Scratchbot: Active tactile sensing in a whiskered mobile robot. In *Submitted to SAB*, 2010.
16. T.J Prescott, M.J. Pearson, B Mitchinson, J.C.W. Sullivan, and A.G. Pipe. Whisking with robots from rat vibrissae to biomimetic technology for active touch. *IEEE Robotics and Automation Magazine*, 16(3):42–50, 2009.
17. Ullman S, Vidal-Naquet M, and Sali E. Visual features of intermediate complexity and their use in classification. *Nat Neurosci.*, 5((7)):682–7, July 2002.