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

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Summary

Rats and other whiskered mammals are capable of making sophisticated sensory discriminations using tactile signals from their facial whiskers (vibrissae) [1]. 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 [6]. 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 [2]. 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.

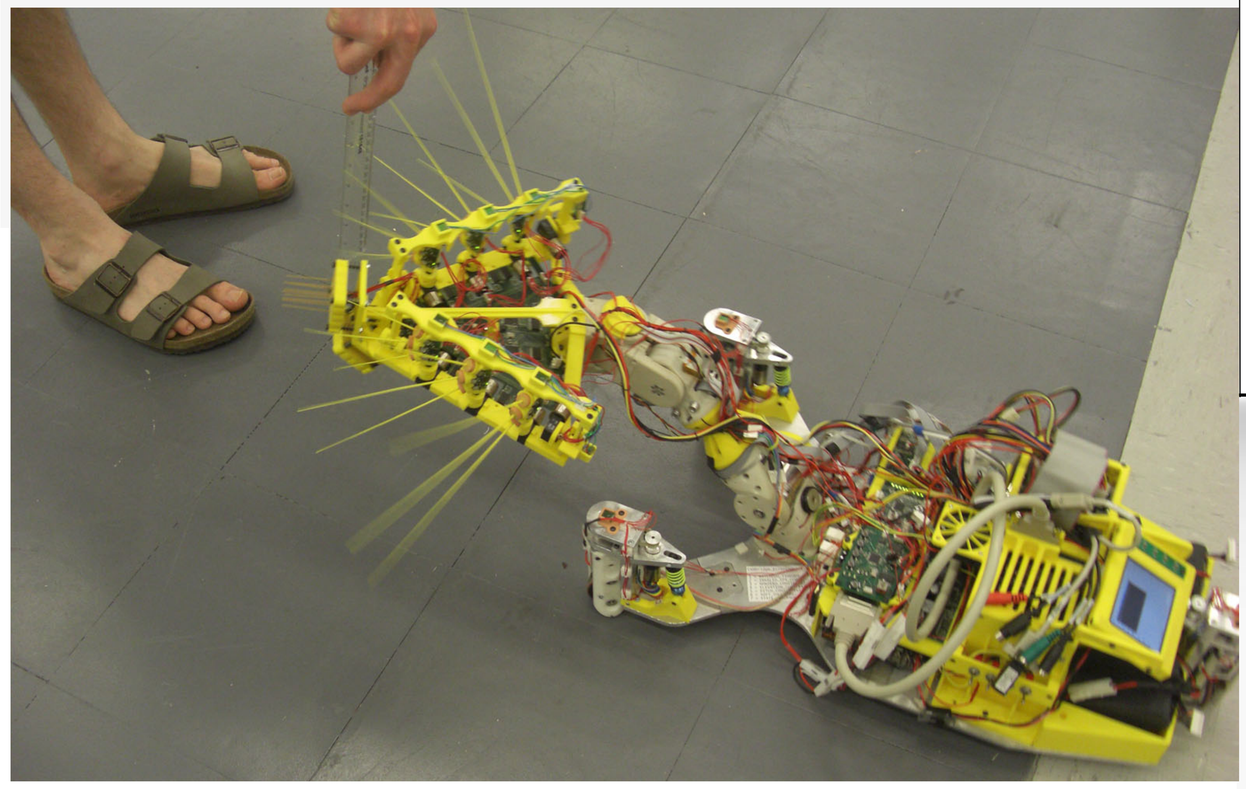
Methods. Our system takes input from a tapered artificial whisker modelled on the shape of a rat whisker at ×4 scale. Transduction at the base is performed using a Hall effect sensor, whilst whisker movement is controlled by a XY positioning robot. An object is carefully moved into the path of the whisker and different speeds and radial distances from the whisker base. Template based classifiers are applied to perform simultaneous radial distance and speed discrimination.

Results. A template based classifier is capable of simultaneous radial distance and speed discrimination. An adaptively generated set of templates compares favourably in performance to that of a hand picked template set.

Conclusion. Previously we have shown [3][5] 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.

Future Work. We are currently working towards integrating the classifiers developed on the XY table to work on a mobile whiskered robot (SCRATCHbot, below [4][8]).

Rigorous testing and comparison of other classifiers using the same dataset will allow us to see what methods are successful under different test conditions.

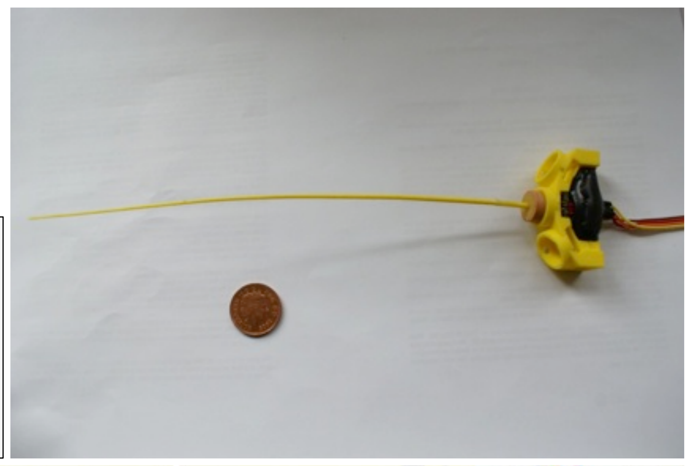


Materials and Methods

The Whisker

ABS plastic whisker shaft (185mm long, 2mm base diameter $E \approx 2.3$GPa) mounted into a polyurethane rubber filled tube

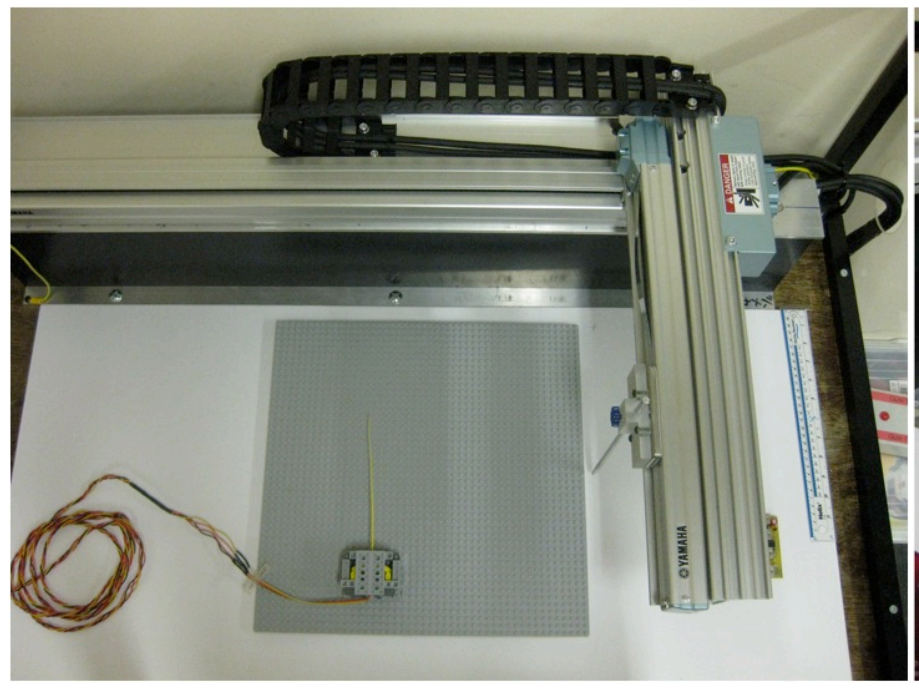
A tri-axis Hall effect sensor IC measures the position of a magnet mounted at the whisker base, providing an accurate measure of whisker base deflection (sampled at 1KHz)

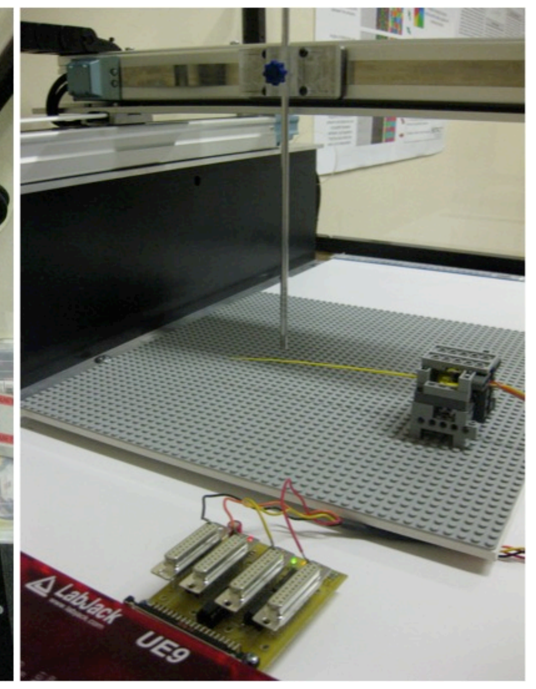


- Max speed: 720mm/s
- X-range: 650mm
- Y-range: 300mm
- Z-range: 210mm
- Repeatability: ± .02mm
- Max load: 1.5kg

The XY positioning robot

Allows precise and highly repeatable control of object-whisker contacts, providing opportunity for generating large datasets





Robot control

Commands and data aquisition performed in MATLAB, via the BRAHMS middleware system

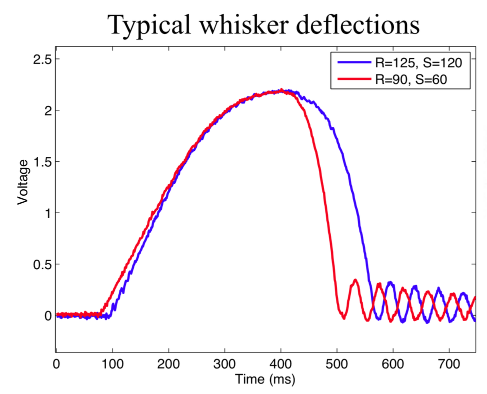
The task

101 radial distances and 26 speeds were sampled

All 2626 combinations were sampled 4 times to provide a training and test dataset

Each trial was aligned to peak deflection, and shortened to only the 325ms either side of the peak deflection (751 data samples in total).

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.

An element-wise sum of squared errors calculation was made between the input I and each template T_i, where n is the length of the template, in samples.

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

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.

Template modification is achieved by taking a weighted mean of the template and the input, where α is the learning rate of the classifier.

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

Results

Template based classifier

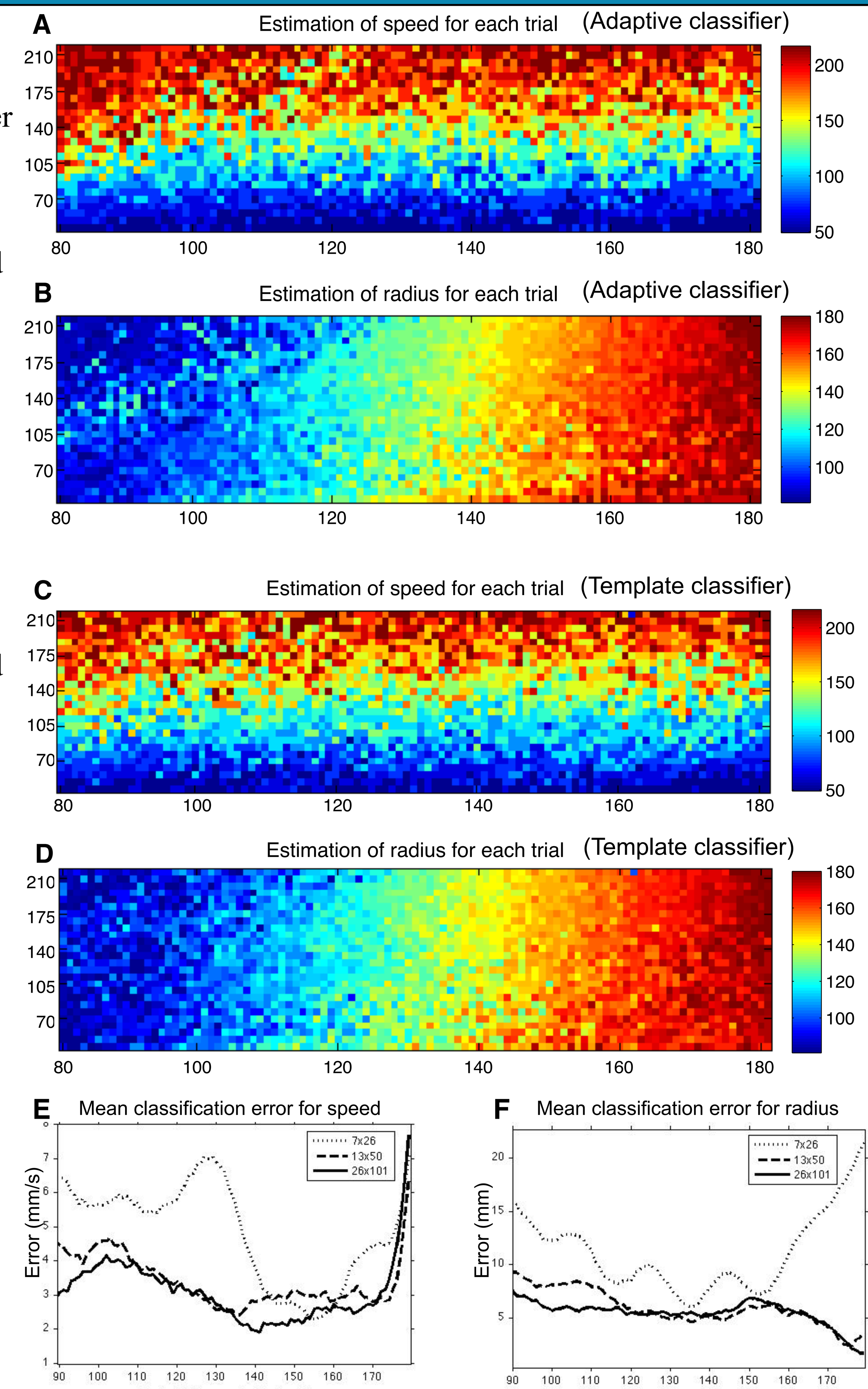
The template based classifier with 13×50 templates was capable of successfully classifying 65% of inputs to within 50mm/s of speed and 10mm of radial distance.

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. (**A-D**) show the results in graphical format. Input signals are shown, arranged for speed and radial distance. Pixel colour indicates the value assigned to that input signal (see colourbar). A completely correct classification of speed (**A**,**C**) would appear as a gradual transition from blue to red vertically along the Y axis, and a corresponding transition from blue to red horizontally along the X axis for correct radial distance detection (**B**,**D**).



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. **E** and **F** show 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 (dashed lines) is good, though the performance of the classifier with the fewest (7x25) templates is less reliable over certain regions of the space.

Together these results suggest classification of whisker contacts is easier over certain regions of the whisker, and at certain speeds, suggesting a rationale for rat whisking behaviour [7]

References

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