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Robust View Based Navigation through View Classification

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Abstract— **Current implementations of view-based navigation on robots have shown success, but are limited to routes of <10m [1] [2]. This is in part because current strategies do not take into account whether a view has been correctly recognised, moving in the most familiar direction given by the rotational familiarity function (RFF) regardless of prediction confidence. We demonstrate that it is possible to use the shape of the RFF to classify if the current view is from a *known* position, and thus likely to provide valid navigational information, or from a position which is *unknown*, *aliased* or *occluded* and therefore likely to result in erroneous movement. Our model could classify these four view types with accuracies of 1.00, 0.91, 0.97 and 0.87 respectively. We hope to use these results to extend online view-based navigation and prevent robot loss in complex environments.**

I. INTRODUCTION

Ants are excellent navigators, successfully using a strategy that involves matching their current view of the environment with a remembered view [3]. We have developed insect-inspired navigational algorithms that emulate view based navigation, showing success in autonomous robotic applications [1] [2]. In these algorithms, a model is trained with panoramic images acquired from a previously traversed route. Subsequently, during route recapitulation, rotated versions of each view, which replicate the view that would be perceived by the robot from that position as it rotates through 360 degrees, are passed into the model. For each rotation, the model outputs a familiarity score, forming a Rotational Familiarity Function (RFF; see examples figure 1 e-h). From these graphs, the rotation with the highest familiarity is taken as the correct heading and the robot moves in this direction. When placed near the training route, this method allows the agent to retrace the route using views alone.

However, route length which can be navigated is limited due to difficulties associated with the reality of outdoor environments. If the robot encounters a view that is unfamiliar to those perceived during training (due to e.g. occlusions from overhanging foliage, getting too close to obstacles) it will still move in a selected direction even if this direction is not very familiar. A second issue occurs where, due to repeated structure in the world, two directions seem equally familiar. Once it has moved off-route, the robot can then be in an unknown area and so continue to move in essentially random directions leading to loss. An indication of the confidence of view recognition based on the RFF could mitigate this, initiating either a search behaviour or stopping navigation before further straying. Indeed, ants themselves present search behaviours when uncertain of direction which can allow them to correct navigation mistakes [4]. We therefore investigate the feasibility of classifying the shape of the RFF, using Principal Components Analysis (PCA) followed by logistic regression, according to whether the current view is known, unknown, aliased or occluded.

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II. METHODS

A. Image Datasets

To train the models, we use outdoor image sets consisting of panoramic, unwrapped grey-scale images, resized to 120 x 25 pixels, to enable 120 orientations of 3 degrees (the angular resolution). A training route (ranging from 4.6m to 10.8m) is manually defined and the views perceived by the agent along this route are used to train an artificial neural network (ANN) using an Infomax learning rule, as described in [5]. These images generate the known RFFs when passed through the trained ANN for testing. In every case, these RFFs provided the correct heading of 0 degrees, thus confirming that they represent the ideal result when a view is known. The unknown image sets are generated by randomly reordering 5 pixel width column portions for each image in the training set. In this way, a statistically similar structure is preserved whilst still presenting the model with a never before seen view. To generate the within-view aliased datasets, where there are two similarly familiar sections in a view as may occur in repetitive environments or when the model is reaching saturation due to too many training images [6], the first half of a view is repeated in the second half. To create occluded images, a 50 % to 65% portion of each training image is obscured with a box of a random intensity. To ensure no sections of any of the manipulated datasets exactly match the training dataset, a small quantity of Poisson noise is applied to all images (mean=200^{-1}). Figure 1 presents example images of each of these cases alongside their corresponding RFFs as output by an Infomax model trained on known images. The known RFFs present a distinct maximum at the correct orientation. The unknown RFFs resemble noise, from which it is apparent that if the maximum is selected the agent is led in a random direction. The aliased RFFs contain two maxima, one for each of the familiar directions. Finally, occluded RFFs present a wide maximum, where a large range of orientations are deemed similarly familiar.

From 13 models each trained on 50 images, a total of 2022 RFFs were generated, with 650 each for the known, unknown and aliased classes and 352 RFFs for the occluded class. These were split into training and test sets using k-fold cross validation, with a total of 4 folds.

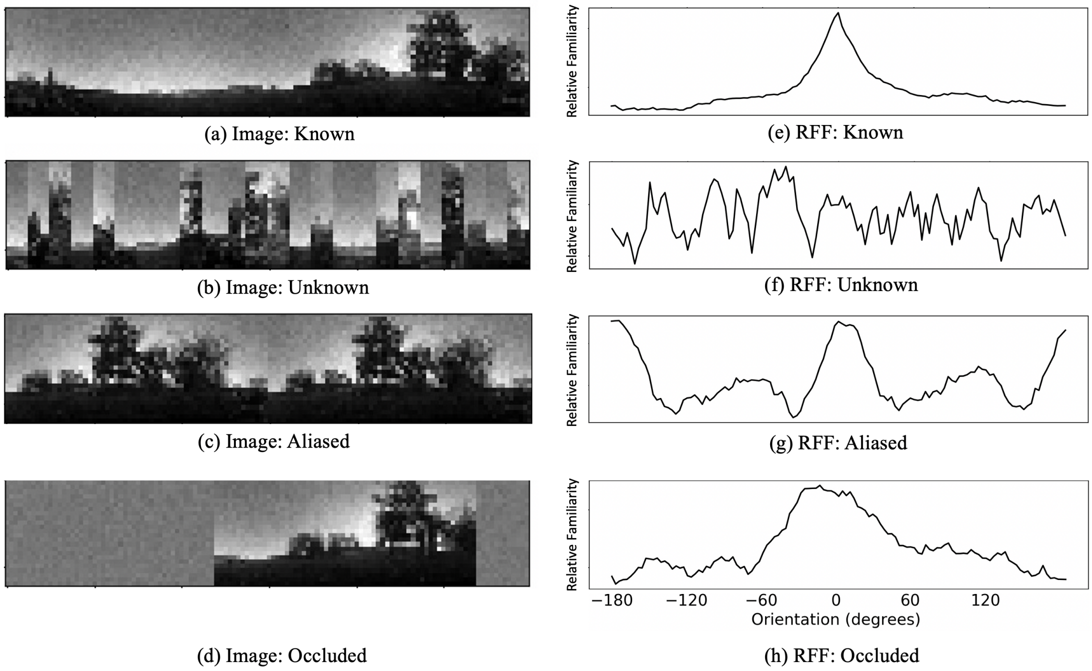

Fig. 1: Example Images and RFFs generated from a trained Infomax model for known (a,e), unknown (b,f), aliased (c,g) and occluded (h,f) views.

B. *Classification Method*

We perform a fast Fourier transform of the RFFs, taking the absolute value of the components to reduce the influence of peak location. The transformed RFFs from the training set are then input to a Principal Component Analysis, retaining the principal components required to explain 95% variance. Following this, we used logistic regression to construct a classifier based on the new basis.

III. Results

In total 5 principal components (PCs) were required to explain 95% variance, accounting for 64.6%, 20.1%, 7.2%, 2.1% and 1.2% respectively when taking the mean across 4 training folds. Using the trained logistic regression model, the mean classification accuracy of the 4 test sets is 1.00, 0.91, 0.97 and 0.87 for the known, unknown, aliased and occluded classes respectively.

In all cases a good accuracy is achieved. For a practical implementation, classification of known images is the most important, as the agent can limit loss by choosing to act based on this alone. Differentiating between occluded, aliased and unknown, as achieved by this model, gives a useful indication as to the reasons for navigation difficulty. The utility of this differentiation might be further improved by generating a range of peak locations in the aliased views, instead of just those with peaks 180 degrees apart.

IV. Conclusions

We have demonstrated successful classification of RFFs according to whether the views are likely to lead to errors in navigation. However, our model is trained and tested on a constrained set of artificially generated views. We are currently implementing this model on an autonomous robot to determine if navigation in outdoor environments is extended by initiating a specific movement behaviour when presented with a poor view. Initially, this could take the form of a scanning pattern or proceeding at a previously determined suitable heading. If continually presented with a number of poor views, the robot might declare itself as lost and performing a backtracking behaviour or send a distress signal. One test environment will be woods where wood ants habitually navigate and where the robot will experience periodic occlusion due to the undergrowth. As well as testing our new model, this will allow us to assess the success of strategies used by ants when faced with uncertain views.

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