

# Biologically Inspired KFLANN Place Fields for Robot Localization

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**Abstract** – This paper presents a hippocampal inspired robot localization model that provides a means for a simple robotic platform with ultrasonic sensors to localize itself. There have been published neurobiological experiments where rats were found to have hippocampal cell activations that positively correlate with the location of the animal [2, 3, 5]. Such activations found in the hippocampal region are usually called Place fields (PF) or Place cells (PC). The Place Field model presented in this paper was designed using a unique K-Means Fast Learning Artificial Neural Network (KFLANN) [13, 14, 15] and establishes a series of localization minima points that act as references for navigation. While such evidence of place cells are seen in hippocampal (CA1) and deep layers of the entorhinal cortex (EC) [4], from a literature search, it is uncertain if any applications were ever designed using this biological evidence. The intent of this paper is to focus on experimental results relevant for a proof-of-concept of robot localization, rather than illustrating a robustly tested navigation system. As such, basic ultrasonic based experiments will suffice. With some experimental results, we show that the KFLANN is suitable for implementing atomic place field vectors (APFV), a data structure to encapsulate localization information.

**Keywords** - Place Field/ Cell Navigation, K-Means fast Learning Artificial Neural Network (KFLANN), Robot Localization, Data Presentation Sequence (DPS).

## I INTRODUCTION

Autonomous unmanned navigational systems have been dependent on localization sensors as a primary means for navigation. In outdoor autonomous systems such as those seen in the DARPA Grand Challenge, most vehicles would make use of combinations of GPS, RADAR, LIDAR and INS [6]. There has also been an increasing amount of research in using only vision to navigate autonomous platforms through spaces such as laboratories and corridors [5]. While these have provided a level of success, the extent of cognitive robotic navigation is far from being solved as a single failure in localization sensors usually leads to a catastrophic system failure. In the midst of man's quest to create robust autonomous robotic systems that can navigate effortlessly through clutter and uncertain environments, laboratory mice used in experiments are revealing secrets of their navigational capabilities. Perhaps

one of the differences in mammalian navigation as compared with robotic navigation is the dependence in cognitive capabilities as opposed to the heavy reliance on sensor technology.

Technological advances need to be complemented with advances in aspects of cognitive processings. We present a method where localization of a robot within a structured space is done using ultrasound information and a compass direction. The discussion omits the navigational aspects of the system as that would require lengthier explanations. A discussion on the KFLANN in Section II is necessary before embarking onto Section III where details of how the Atomic Place Field Vector (APFV) is used for localization.

## II K-MEANS FAST LEARNING ARTIFICIAL NEURAL NETWORK (KFLANN)

### A.. KFLANN Network Architecture

The KFLANN architecture resembles that of the ART neural network developed by Carpenter et al [9] and it utilizes the winner-take-all selection often associated with the Kohonen networks [10]. The architecture is depicted in Fig. 1 and comprises of two layers, namely the Input Layer (F1) and Output Layer (F2). Layer F1 is the direct map of the input patterns. The weighted connections between the input layer and output node are represented by the input vectors entering the network through the F1 layer. The Output layer is dynamically created to accommodate new exemplars from F1 that do not have representative patterns already existent in the F2 layer. The KFLANN algorithm requires an initialization of two parameters, namely Vigilance  $\rho$  and Tolerance  $\delta$ .

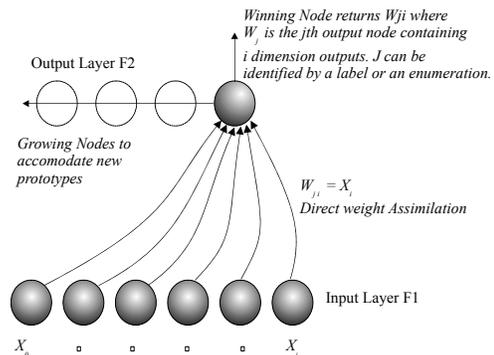


Fig. 1 KFLANN architecture.

The two KFLANN network parameters are key to obtain a suitable clustering outcome. This paper will utilize the Euclidean distance metric as it is more suitable for odometric references.

### B. KFLANN Network Parameters

The KFLANN consists of 2 main network parameters. These are the Vigilance ( $\rho$ ) and Tolerance settings ( $\delta$ ). Like the ART networks, the Vigilance factor ( $\rho$ ) parameterizes the attention aspect of the network. The Tolerance setting ( $\delta$ ) provides a means to perform neighborhood competitions within the ART type model possessing a similar behavior to the type of nearest neighborhood competition found in the Kohonen networks. The KFLANN differs from the ART in this manner. Another property that differentiates the KFLANN from other networks is the possibility of heuristically deriving suitable values of the network parameters from the characteristic of the dataset presented. It is therefore necessary to possess the store of data exemplars before processing. It again differs from the ART in this aspect as the ART does not require an existing dataset, but executes on-line.

### C. Vigilance ( $\rho$ )

The Vigilance ( $\rho$ ) is a parameter that originated from Carpenter et al [9]. It was designed as a means to influence the matching degree between the prevailing exemplar and the of a long term memory trace. In the KFLANN, it functions similarly where higher values of  $\rho$  will enforce a stricter matching criteria and for smaller  $\rho$  results in a relaxed matching criteria. The  $\rho$  in the KFLANN is similar and is used to determine the number of the attributes in the presiding exemplar that are similar to the selected long term memory trace. The Vigilance formulation is given by equation (1).

$$\rho = \frac{f_{match}}{f_{total}} \quad (1)$$

Where  $f_{match}$  is the number of the features needed in order to be classified as a same cluster and  $f_{total}$  is the total number of features.

This  $\rho$  is analogous to the human attentive behavior where a detailed scrutiny of information will generate finer resolutions in discriminative capabilities.

### D. Tolerance $\delta$

While  $\rho$  governs the global variation in the input features, the Tolerance,  $\delta$ , is a localized control, affecting only individual features (elements of the exemplar vector). The Tolerance setting,  $\delta$ , is the maximum allowable range that

the specified feature is allowed to fluctuate. The standard deviation of the specific feature turns out to be a suitable data-driven heuristic that provides an autonomous means to setting the  $\delta$  values. By definition, the standard deviation is the measurement of dispersion of sampled variables from the mean. The tolerance computation using the typical standard deviation ( $\sigma$ ) is given in equation (1). At times, when clusters are not well defined, a  $\sigma/2$  may be more suitable

$$\delta_i = \sigma_i = \sqrt{\frac{(X_i - \mu_i)^2}{n}} \quad (1)$$

Where  $X_i$  is the  $i^{th}$  feature spans over  $n$  number of data patterns and  $\mu$  is the respective mean value.

### E. The Algorithm

The algorithm of the KFLANN is presented in this section. Its execution is similar to typical Leader-Type algorithms mentioned by Hartigan [12]. The distance metric used is the Euclidean distance.

#### Notation

$\rho$ : vigilance value

$\delta_i$ : tolerance value of the  $i^{th}$  attribute

$n$ : number of input attributes

$I_i$ : the  $i^{th}$  input node

$W_{ji}$ : weight connecting the  $i^{th}$  input node and the  $j^{th}$  output neuron

$D[a] = 1$  if  $a > 0$ .

Otherwise  $D[a] = 0$ .

1 Initialize network with  $\rho$  between 0 and 1. Determine and set  $\delta_i$  for  $i = 1, 2, 3, \dots, n$ . The values of  $\rho$  and  $\delta$  affect the behaviors of the classification and learning process.

2 Present the next pattern to the input nodes. If there are no output clusters present, GOTO 6.

3 Determine the set of clusters that are possible matches using equation (2). If there are no output clusters GOTO 6.

$$\frac{\sum_{i=1}^n D[\delta_i^2 - (W_{ji} - I_i)^2]}{n} \geq \rho \quad (2)$$

4 Using criteria in equation (3) determine the winning cluster from the match set from Step 3. Normalize  $W_{ji}$  and  $I_i$ . The following distance is calculated between the normalized versions.

$$winner = \arg \min_j \left[ \sum_{i=0}^n (W_{ji} - I_i)^2 \right] \quad (3)$$

- 5 Winner is found. Add vector to the winning cluster. If there are no more patterns, GOTO 7. Else GOTO 2.
- 6 No match found. Create a new output cluster and perform direct mapping from input vector into weight vector of new output cluster. If there are no more patterns, GOTO 7. Else GOTO 2.
- 7 Re-compute cluster center using K-means algorithm. Find the nearest vector to the cluster center in each cluster using equation (3). Place the nearest vector in each cluster to the top of the training data and GOTO 2.

### F Topological Clustering Behavior of KFLANN

An evident property of the KFLANN network is in the clustering consistency of the algorithm. While many clustering algorithms exist in literature today, few are able to provide consistent cluster centroids independent of the data presentation sequence (DPS) [13, 14, 15].

KFLANN achieves its consistent clustering behavior by performing a reshuffling of the original data in Step 7 of the algorithm described in Section III E. The reshuffling process involves the movement of data point closest to the individual cluster mean to top positions of the data list. This process essentially changes the seeding sequence on the data presentation sequence (DPS), but maintains the rest of the data in the original list position. The entire clustering process is then repeated on the new reshuffled data list, replacing the old dataset with the new reshuffled set. The results of the first iteration clustering is thus discarded and a completely new clustering is repeated using the new reshuffled data list. Termination of the clustering cycles can be invoked after all significant changes to the cluster centroids cease. In experiments conducted, it was empirically found that a maximum of 5 iterations was needed for the centroid stabilization process.

Geometrically, this reshuffling process changes the centroid seed positions in each subsequent epoch, spreading the centroids across the problem space before individual exemplar cases are presented. The two class Euclidean  $R^2$  example in Fig. 2 is used to illustrate how the KFLANN reshuffles data patterns and how centroid stability is achieved. Both classes are represented by different point markers. Assume that the initial data points presented start with  $P_1, P_2, P_3$  and  $P_4$ . By virtue of the presentation sequence, the algorithm begins by adopting the 4 data points as centroids.

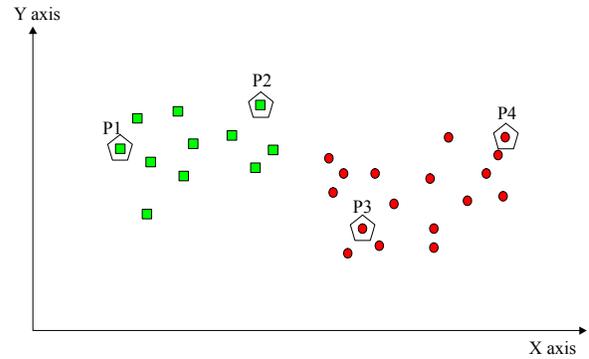


Fig.2 A 2D distribution of data points

The first iteration of the KFLANN clustering produces 4 clusters as shown in Fig. 3. Centroids in each cluster are subsequently identified and the arrows in Fig. 4 indicate the direction which the new centroids would tend towards. This movement can be equated with a hill climbing process, where the point of central tendency is the optimal point in the space.

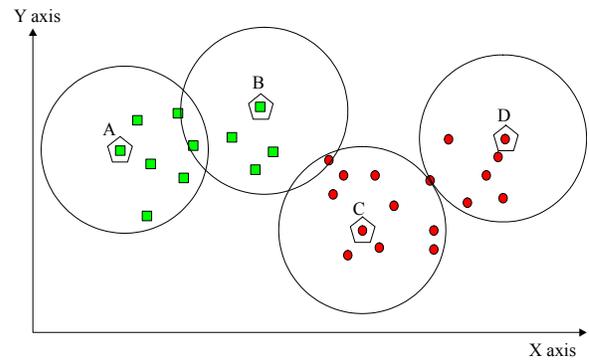


Fig 3 Initial formation of centroids in first iteration

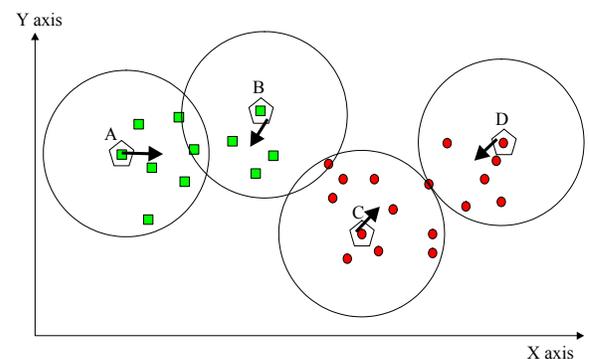


Fig. 4. Arrows showing the movement tendency of the reshuffled centroids

The re-computation of means after the first epoch shown in Fig. 4 leads to the shuffling of the cluster means to the top of the next data list. In the next iteration shown in Fig. 5, the points at the top become the new points that seed the problem space with clustering centers. The arrows again indicate the migration path of the centroids. An

apparent movement towards the central tendency of the data is achieved.

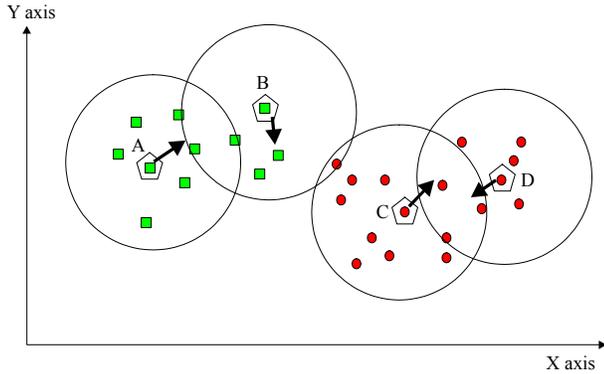


Fig. 5. Centroids continue to shift to the region of central tendency in each subsequent reshuffle.

As the iterations continue, the means begin to converge to specific central tendencies in the data space, forming consistent clusters. The movements of centroids can sometimes lead to merging of clusters as seen in centroids A and B of Fig. 6. Cluster B is subsumed by cluster A. Note that centroids C and D reach a limit for movement because the outer points in their clusters forbid the two clusters from merging. At the last iteration, three clusters were created with stabilized centroids and the clusters coverage is shown in Fig. 7.

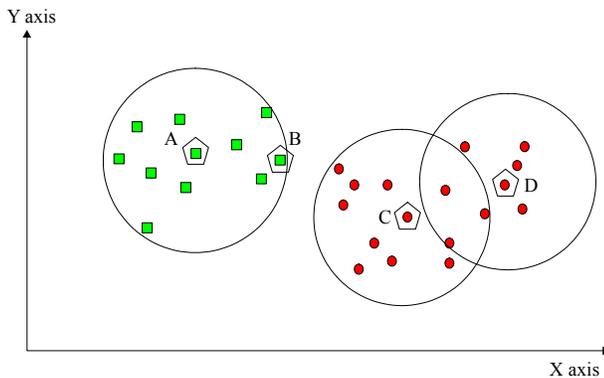


Fig. 6. Arrows showing the movement tendency of the reshuffled centroids

The illustration in Fig. 7 indicates the cluster representation using circles, instead of the likelihood of irregular representations of the cluster. The data sequence reshuffling introduced to form the KFLANN algorithm allows the data pattern sequences to be in any initial order. As compared to clustering without reshuffling, the resulting clusters using KFLANN tend to be a consistent and stable, deviating minimally between independent runs. Results of the consistency tests can be obtained from Wong et al [14, 15], where the authors showed a tighter

standard deviation in KFLANN reshuffled clusters, compared to those without reshuffling.

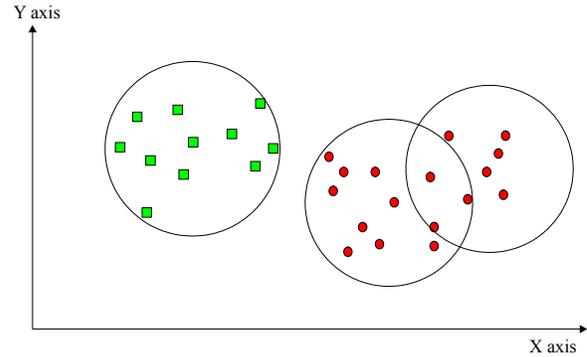


Fig.7. Final Iteration Of The KFLANN Clustering On The 2D Exemplar Dataset

### G. Implications of KFLANN Clustering Consistency

It is now important to understand the relevance of the need for consistent clustering. We would like to loosely analogize the simplistic concept from the 2D Euclidean problem discussed with an image recognition problem, where the objective is identifying apples and pears. If indeed the human recognition capability is built upon order dependent learning, then there should exist, a diverse opinion to classification of apples and pears. We argue that a fundamental necessity in the KFLANN algorithm is its ability to maintain a relatively consistent set of centroids regardless the DPS and it is only with such consistency that Hippocampal Place Fields (PF) or Place Cells (PC) can be effectively derived.

### III KFLANN PLACE CELL COMPUTING

Unlike the typical autonomous vehicle path planning methods, mammals have a very different concept to navigation. While the common method for AUGV path planning is based on grid maps and traversal weights, mammals are known to use place cells (PC) or place fields (PF) [7]. Place cells which are occasionally used interchangeably with place fields were first discovered by O’Keefe et al [16]. Through the years of continuous research, it is now known that there is a systematic way by which the mammalian hippocampus (CA1) is encoding spatial information which provides the means to recognize places. Some of the clinical experiments indicate a distinct firing rate of CA1 cells as the animal wanders across familiar paths [2, 4]. Other prominent experiments include the Morris Water Maze and the rotating platform [3, 17].

#### A Place Field Construction using the KFLANN

This section discusses how PFs for robotic localization applications can be designed with the help of KFLANN. A

reason for this success is the inherently lean algorithmic structure that provides for high speed processing [13].

An illustration of the some sensor locations on a simple robot model is shown in Fig. 8. This basic robotic model operates on 8 directional ultrasonic sensors and a digital compass. Through a simple manipulation of the sensor inputs, a 12 input Atomic Place Field Vector (APFV) is synthesized. While this is a basic example with 8 ultrasonic sensor inputs, these can be combined with other more precise sensors.

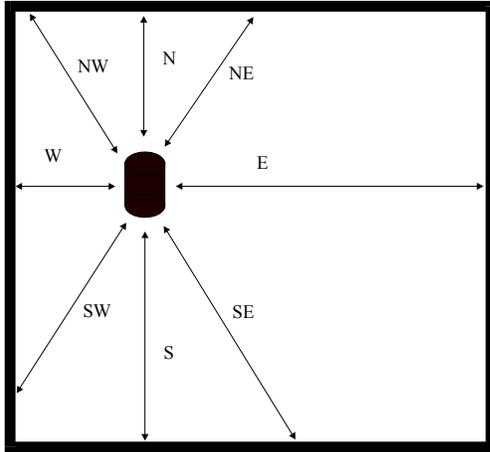


Fig. 8 Plan view of the robot using 8 directional ultrasonic sensors to determine the dimension and localization information within a confined space.

The initial 8 inputs to the APFV consists of the following ultrasonic readings from the positions on the robot frame N, S, E, W, NE, SE, NW, NE. A subsequent 4 readings are derived from summing readings taken from opposite sensors, ie. N+S, E+W, NE+SW, NW+SE. The compass directional information is used as a means to orientate the sensors to populate a common fixed direction APFV. Thus, regardless the robot's direction, only a single consistent APFV is created for any given location.

Three experiments were carried out with this configuration to test the effectiveness of the APFV. The goals of these experiments were

- (i) Examine the localization efficacy of FLANN APFV.
- (ii) Determine if confounding environments can occur in KFLANN APFV
- (iii) Examine how KFLANN APFV growing behavior is consistent with mammalian navigational concepts.

### B Localization Efficacy of the KFLANN APFV

The first objective was to determine the localization capability of the robot within a single large open space.

The dimensions of the room need to be within the operating range of the sensors. Fig. 9 shows the results of the experiment when the robot was manually driven around the room 5m square room to collect sensor information. Note that the creation of new clusters was a sporadic process where new clusters were constantly created as it entered unfamiliar territories.

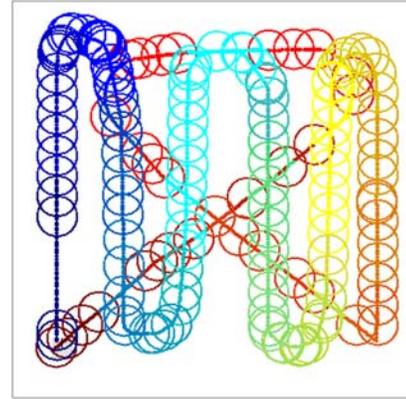


Fig. 9 Initial clustering of visited points into regions of reference (Square Room)

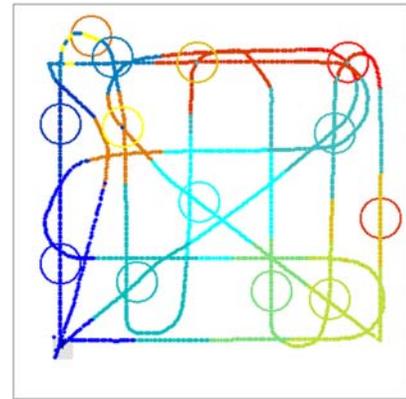


Fig. 10. Reduced Place cell representation after consolidation (Square Room)

Fig. 10 shows the clusters after consolidation of information using the KFLANN reshuffling. Note that the number of clusters was reduced from 143 clusters in Fig. 9 to 13 clusters in Fig. 10 after consolidation.

The circles help highlight the centroid positions, but do not indicate the field of influence. This field of influence cannot be visualized here because each APFV is a 12 dimensional vector. All that the circle can implicate is the estimated position of the centroid. In this APFV representation in autonomous navigation, it is thus possible to relate actual positions of the robot to approximate locations of the robot. This is consistent with the way mammals navigate, where localizations are referenced to surrounding information, rather than a global position such

as GPS data. It is also consistent to state that the precise position of the mammal is of little importance, but estimated references were sufficient for successful navigation. This provides a more robust means for performing navigation, as compared with grid based planning methods where precision grid positions are often used to autonomously navigate vehicles across the terrain.

### C Confounding Atomic Place Field Vectors (APFV)

One concern in PF computations is the possibility that two places possess the same APFV definition. This is caused by the possibility of having two locations with the exact sensor readings. The experiment that follows shows that this possibility indeed exists. A larger facility was used to test the effectiveness of APFVs and to illustrate the possibility of confounding spaces. Unlike the first experiment where the APFVs were used to localize a single room, larger facilities will tend to provide more opportunities for confounding the APFVs. Fig. 11 shows the experimental results of an initial run through a 20m long corridor.

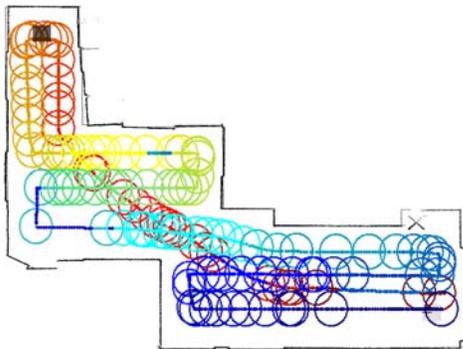


Fig. 11 A 20m long corridor with complex structures

A total of 119 clusters were formed in this run. After the reshuffling process, the number reduced to a consolidated set of 24 clusters. This is illustrated in Figure 12.

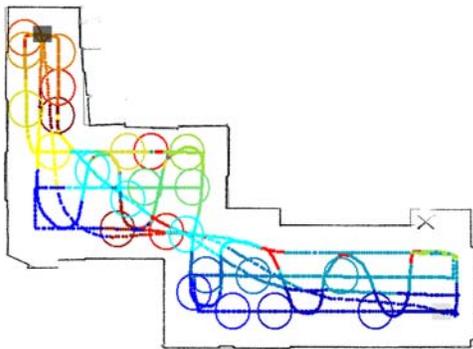


Fig. 12 Reduced clusters after KFLANN APFV reshuffling.

As expected, several confounding APFVs were located and through an examination of the APFV configuration, we show that such possibilities exist. Fig. 13a and Fig 13b show set of confounded locations

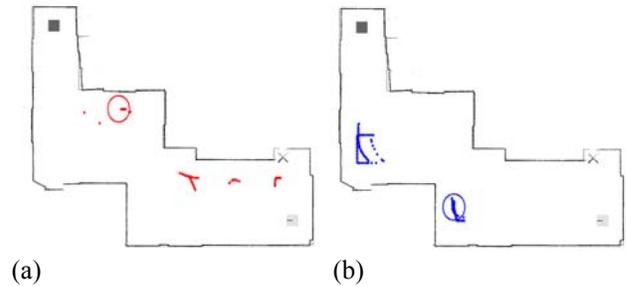


Fig 13 Areas where the APFV had confounding locations.

It is noted that APFV definitions can be confounded in several different locations. This is because the 12 dimensional input vector received at the locations may bear similar magnitudes and general similarities. Thus, the ultrasonic information is insufficient to differentiate the two confounded places. In Fig 13a, several spots away from the original centroid are seen. This is because the spots share the same 12 dimensional APFV centroid, marked as a circle. This is also seen in Fig 13b where the two angled corners of the room bear similar ultrasonic characteristics. One possible solution to this is to increase the dimensional inputs of ultrasonic sensors. However, we have chosen not to pursue this avenue because we believe the hippocampal and entorhinal cortex do resolve confounding issues at the level of the APFV, but address navigation at a higher hierarchical level. However, we know from neurological research that APFV equivalents do exist but are not by themselves complete. APFVs are a means by which a more complex set of parameters are used in order that navigation can be achieved without confounding. The solution to this confounding issue is not discussed in this paper.

### D Stable Clustering and Generalization

As discussed in the section on KFLANN, the algorithm is able to consistently derive similar centroids regardless the DPS. We mentioned that is not always true for other algorithms as many existing algorithms are sensitive to DPS. The experiment in III B highlighted how the centroids were first created as the vehicle moved through the single large room. We note that if the robot was allowed to reorganize using the reshuffling feature in KFLANN, the resultant clusters will begin to perform an optimization and the centroids will begin to shift, eventually providing a new representation of the place. This result is shown in the two cases of Fig. 10 and Fig. 12, where the reshuffling process performed a complete rearrangement of centroids. The clusters were reduced

from the original 143 to 13 and 119 to 24 respectively. This observation is important because the centroids can also be deemed as a stereotype of the place or location. Having a consistent stereotype is therefore essential for common place recognition and ascertaining the consistency of information between multiple robots and multiple runs. It is thus important that across platforms, for means of communicating positions, localization can generally be repeated.

Fig 14 shows the robot platform where experiments are being executed or simulated on.



Fig. 14 The experimental platform

## IV DISCUSSION AND CONCLUSIONS

### A APFV and the hippocampal equivalent

Atomic Place Field Vector (APFV) was coined out of the construction that it is the basic unit by which actual cognitive navigation can be achieved. This is designed specifically for this simple robotic platform. Frank et al [4] provided significant evidence that hippocampal (CA1) interactions with the entorhinal cortex (EC) exhibit different firing rates even when the rat was in the same location. This result is contrary to the theory that place cells were coding only place positions. See Marr 1971 [19]. In their experiments with rat hippocampal recordings, it was noted by Frank et al that while the rat location was important, equally important was the place of origin and the target destination of the rat. This was deduced when hippocampal cells did not always fire at the same rates even though the rat was at the exact position of the given cell recording. However they noted that firing was consistent based on the rat's previous location, current position and intended destination. It is therefore sufficient at this point, to present a means to code a specific location

using the APFV with KFLANN without considering the before and after positions of the rat. We believe that our quest for a successful PF navigation can be achieved by manipulating the existing APFVs in a hierarchical manner (not discussed in this paper).

### B Confounding results in the APFV

The APFV confounding situation can only be partially appreciated from the Euclidean representation in the figures provided. Each APFV is a 12 dimensional vector consist of the directional sensor information obtained for the robot. The confounding regions shown in Fig. 13a and Fig. 13b provide insight into the reasons for the confusion. Note that because the conditions of the APFV at the points are very much similar, as a result, confounding circumstances arise. Confounding can sometimes be caused by the generalization of the KFLANN. While it is the characteristic of the KFLANN algorithm to generalize across 12 input vectors so that it is able to cater to noise in the ultrasonic readings, it happens to be an issue of overgeneralization. Here we see that due to a desire to increase the robustness, it has added in compensations that increase the possibility of confounding similar looking spaces. We believe that this issue will be addressed as a more elaborate hippocampal model is designed, where combinations of APFVs are knit together.

### C Optimization of the centroids (Motivation in REM and NREM)

An observation on the initial robotic discovery phase is the generation of a considerable number of clusters. After a time of consolidation through reshuffling in KFLANN, the number of clusters reduced significantly.

We would like to compare this with the biological equivalent of results obtained from Louie et al and Wilson [11, 1]. While it is difficult to examine cluster stereotypes in neurobiological studies, the investigators did note that the experimental rats exhibited a form of temporal replay of the places visited. During the Rapid Eye Movement (REM) sleep in the rat, hippocampal (CA1) neurons were found to replay the sequence of activity that had been experienced on a timescale of tens of seconds to minutes. These patterns and extended patterns of ensemble response could be directly matched with corresponding patterns that had been recorded during training (discovery) on a simple behavioral task.

We would liken the process of Hippocampal replay as a means for the robot to reorganize the locations to perform a stereotyping process. This stereotyping process eventually optimizes the feature space of the room so that there is a smaller set of features that represent the different locations.

#### D A new paradigm for navigation (PFV vs Grid)

We have presented here a new paradigm by which robots may be localized by environmental features. A series of experimental results were presented to provide a proof-of-concept. While the AFPVs show considerable confounding possibilities, we see this as the building block towards a comprehensive place cell navigation neural system. As compared with the grid based navigational algorithms such as those presented in Ibanez-Guzman et al [7], APFVs have a potential of providing a more robust platform for navigating in highly uncertain environments without complex localization sensors. While we have presented an approach indoors with very simplistic and course grained sensor array, the concept extends to the entire set of highly accurate sensors.

#### E Future work

The present work is confined to algorithmic processing of a neural inspired architecture. The focus has been on algorithms with sensory responses which are physical. We intend to push this work towards navigation using APFVs and provide for a means where cognitive decisions can be made by the robot. It thus seems inevitable, and a natural process that future work advances into other aspects of human psychology, in particular, emotion.

Despite controversy in the field about the dominance of the emotion as a motivating stimulus, most accept emotion as a trigger to action. Can the artificial device that is now capable of responding to a physical or cognitive stimulus, respond to an emotional trigger? What would be the role of emotions in their cognitive responses? What will trigger robots to make adjustments to their original intended goal? These are just some questions that the current research is probing into.

#### REFERENCES

- [1] M. A. Wilson, "Hippocampal Memory Formation, Plasticity and the Role of Sleep", *Neurobiology of Learning Memory*. 78, 565-569 (2002)
- [2] J. Bures, A. A. Fenton, Yu. Kaminsky and L. Zinyuk. "Place Cells and Place Navigation", *Proceedings of the National Academy of Science*, Vol 94, pp 343 – 350, January 1997. *Psychology*.
- [3] R.G.M. Morris, P. Garrud, J.N.P. Rawlins and J.O. O'Keefe. "Place Navigation Impaired in Rats with Hippocampal Lesions", *Nature*, Vol 297, pp 681 – 683. June 1982
- [4] Loren M. Frank, Emery N. Brown and Matt Wilson. "Trajectory Encoding in the Hippocampus and Entorhinal Cortex. *Neuron* Vol 27, 168 – 178, July 2000.
- [5] A.J. Davidson and D.W. Murray. "Mobile Robot Localization using Active Vision". *Proc 5<sup>th</sup> European Conference on Computer Vision*, Freiburg, Germany, 1998 pp 809 – 825 (Springer LNCS Vol 1407, Vol II)
- [6] <http://www.darpa.mil/grandchallenge05/TechPapers>
- [7] J. Ibanez-Guzman, J. Xu, A. Malcom, Z. Gong, C.W. Chan, L.P. Tay. "Autonomous Armoured Logistic Carrier for Natural Environments", *IROS Japan*, October 2004 .
- [8] N Winters, J. Santos-Victor, "Visual Attention-Based Robot Navigation using Information sampling", *IROS Hawaii*, October 2001.
- [9] G. A. Carpenter and S. Grossberg, A massively parallel architecture for a self-organizing neural pattern recognition machine, *Computer Vision, Graphics, and Image Processing*, Vol. 37, 1987, pp.54-115.
- [10] T. Kohonen, Self-organized formation of topologically correct feature maps, *Biological Cybernetics*, Vol. 43, 1982, pp.59-69.
- [11] Louie K. and Wilson M. A. (2001). Temporally structured REM sleep replay of awake Hippocampal ensemble activity, *Neuron*, 29:145-156.
- [12] J. Hartigan, *Clustering algorithms*, New York: John Wiley & Sons, 1975.
- [13] L.P. Wong, L. P. Tay and Xu J. Centroid Stability with K-Means Fast Learning Artificial Neural Networks. *IJCNN Portland 2003*.
- [14] L.P. Wong, L. P. Tay and Xu J. "Hierarchical Fast Learning Artificial Neural Network", *IJCNN Montreal 2005*.
- [15] L.P. Wong, L.P.Tay and Xu J. "A Novel Hybrid Learning Scheme for Pattern Recognition", *IJCNN Montreal 2005*.
- [16] J. O'Keefe and J. Dostrovsky. "The Hippocampus as a Spatial Map", *Brain Research* 34, 171 – 175 (1971)
- [17] P.D. Martin and J. O'Keefe, "Place Field Dynamics and Directionality in a Spatial memory Task", *Brain Research* 783, 249 – 261 (1998)
- [18] D. Marr, "Simple Memory: a Theory for Archicortex.", *Philosophy Transactions, Royal Society London*, 262 pp 23 - 81 (1971).