# Report

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- Research areas
- Feature selection based on Brain Storm Optimization
- Future research plan

# Research areas:

- Robotics & Sensors
  - UAV control system
  - UAV fault detection and monitoring system
  - Human motion recognition

- Machine learning and evolutionary algorithms
  - Feature selection
  - Classification

# Robotics & Sensors

## 1. Unmanned aerial vehicle (UAV) control system

Jiang, F., **Pourpanah,** F., Qi, H., (2018). Design, implementation and evaluation of a neural network based quadcopter UAV system. *IEEE Transactions on Industrial Electronics,* Manuscript ID: 18-TIE-2102 **(major revision)**

## 2. UAV fault detection and condition monitoring

**Pourpanah, F.,** Zhang, B., Ma, R., Qi, H., (2018). Anomaly detection and condition monitoring of UAV motors and propellers. *IEEE conference on Sensors.* **(accepted)**

## 3. Human motion recognition

**Pourpanah, F.,** Zhang, B., Ma, R., Qi, H., (2018). Non-Intrusive human motion recognition using distributed sparse sensors and the genetic algorithm based neural network. *IEEE conference on Sensors.* **(accepted)**

# Feature selection

- **Feature extraction** and **feature selection** are two important pre-processing steps in Data Mining, specifically for solving classification problems.

- **Feature extraction** extract features from raw data.
- **Feature selection** is a process of removing redundant and irrelevant features from **extracted features** to achieve better accuracy and/or reduce the model complexity.

- Nevertheless, it is a difficult task to select a relevant and useful feature subset, particularly with **high-dimensional** features due to a **large search space**.

# Feature selection

- Feature selection can be categorized into three groups:
  - **Filter based** methods use characteristics of training samples, i.e., distance.
  - **Embedded based** methods integrate search mechanism during learning.
  - **Wrapper based** methods use a classifier to operate as feedback mechanism to evaluate the effectiveness of the various feature subsets.

- **Wrapper-based methods** are more effective, but they are more complex and require a longer execution time.
- Traditional wrapper-based methods such as sequential forward selection (SFS) and sequential backward selection (SBS) have shown promising results, but they are computationally too expensive.
- To solve this limitation **Evolutionary Computation** based methods such as GA, PSO are used.

# Feature selection based on Brain Storm Optimization for data classification

Thus, wrapper-based methods require two elements:

- A classification algorithm
- A search mechanism

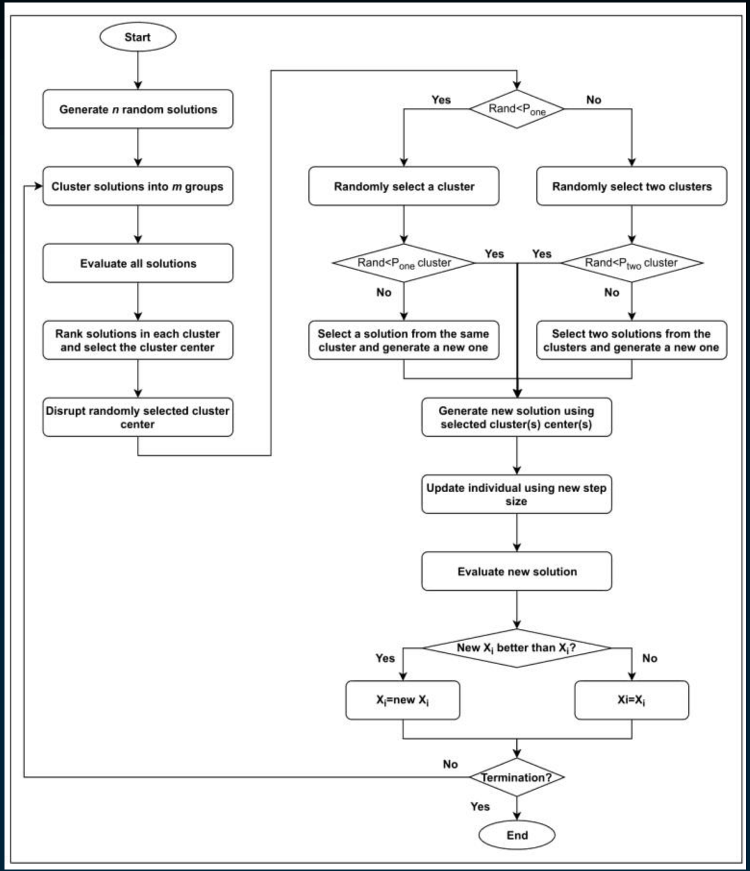
- Fuzzy ARTMAP (FAM), which is a supervised learning method with the capability of incremental learning, is used as classification algorithm
- BSO is used to find an optimal feature subset.
  - Error rate is used as fitness function

# Brain Storm optimization (BSO)

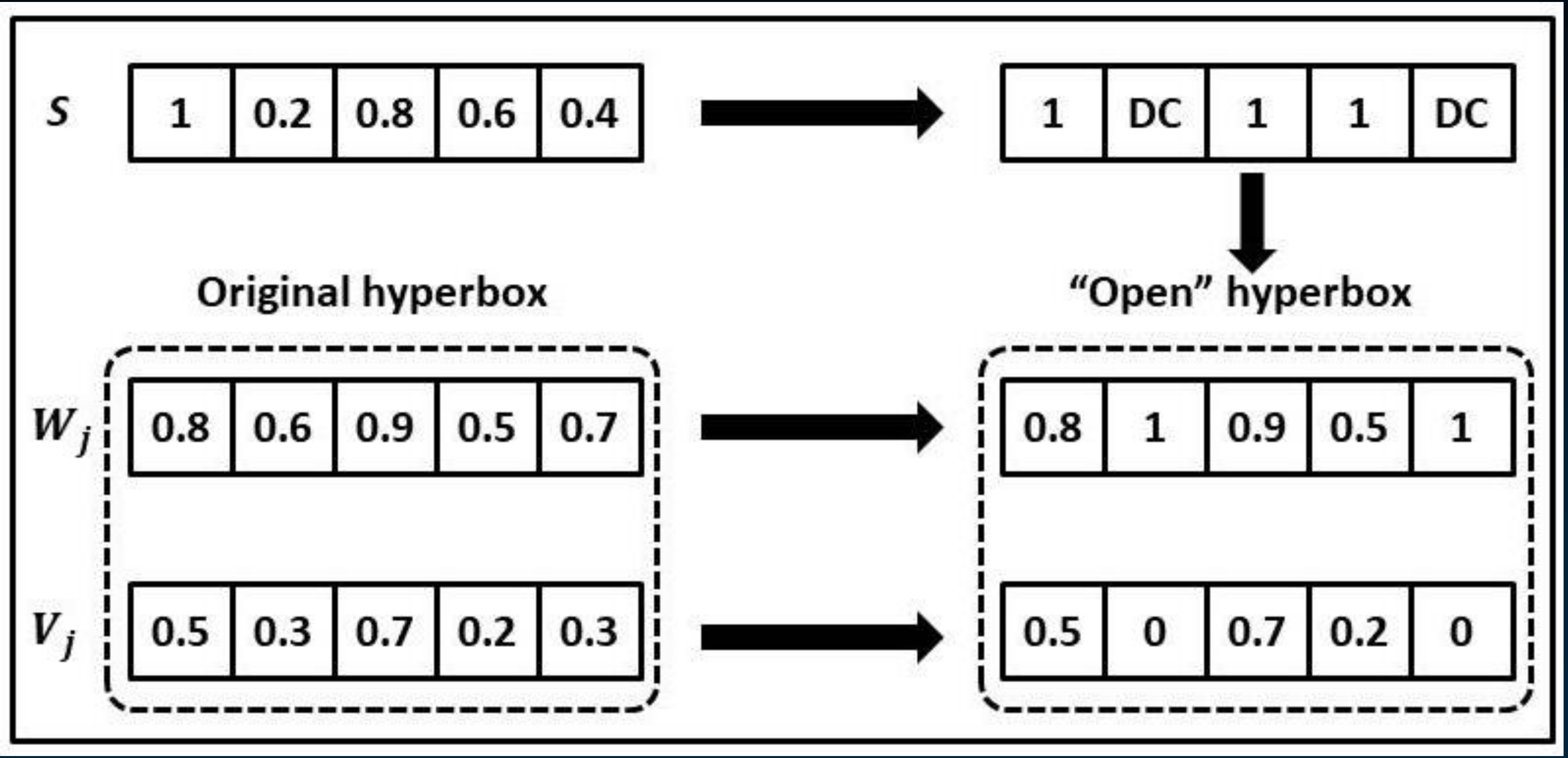
- BSO is a new and effective swarm intelligence method inspired by human brain storming process.

**Algorithm 1:** The procedure of the original BSO

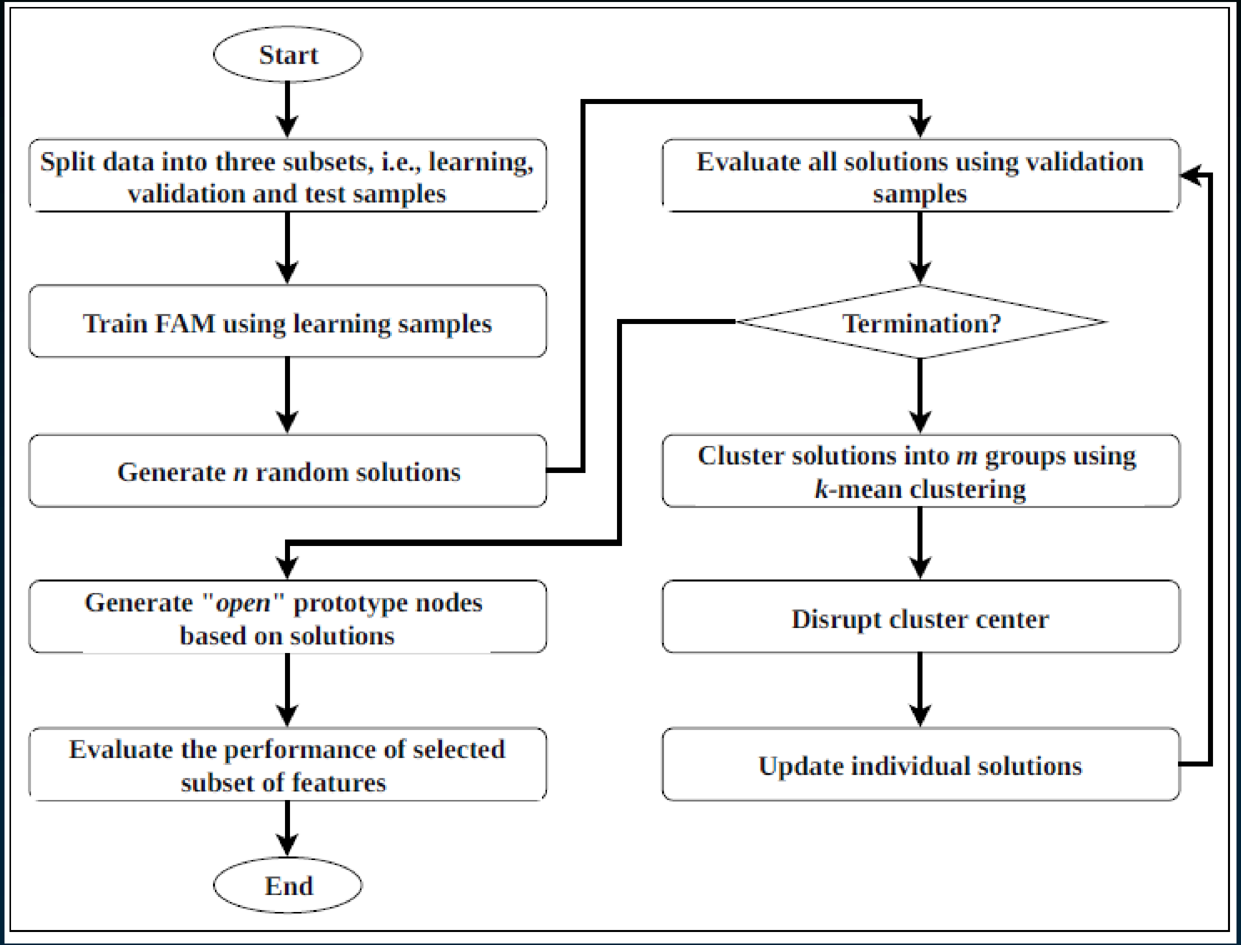
```
Population initialization;
while not terminated do
    Evaluating individuals;
    Clustering individuals;
    Disrupting a cluster center;
    Updating individuals;
Output individuals;
```



# An example of generated solution, original node and open porotype node



# Proposed FAM-BSO



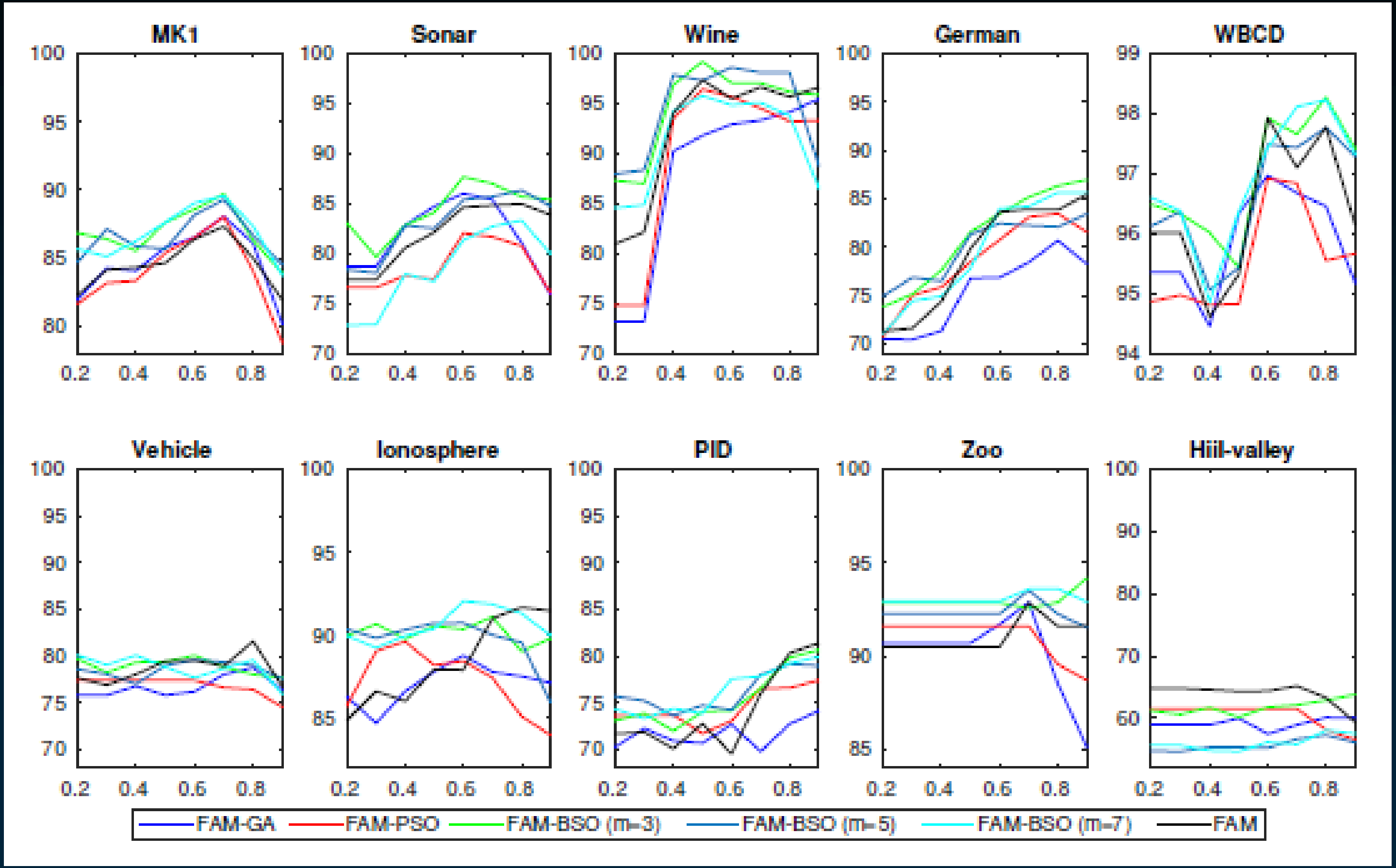
# Accuracy rates

| Data set | FAM-BSO (best) | PSO(3-1) (best) [43] | PSO(4-1) (best) [43] | BPSO-2 Stage(best) [57] | U-FAM [27] | ACO-ER [1] | GP$mtfs$ [32] |
|---|---|---|---|---|---|---|---|
| MK1 | 84.42 (88.19) | 85.51 (90.21) | 84.62 (90.21) | **85.70** (89.51) | - - | 79.53 | - |
| Sonar | **87.97** (90.74) | 78.03 (85.71) | 77.40 (87.30) | - | 72.00 | - | 86.26 |
| Wine | **97.15** (100.0) | 96.62 (98.77) | 96.15 (98.88) | 96.94 (100.0) | 89.00 | - | 94.82 |
| German | **82.92** (84.93) | 69.13 (71.67) | 69.27 (74.33) | 68.93 (73.67) | - | 70.17 | - |
| WBCD | **96.49** (98.83) | 93.02 (94.15) | 93.78 (94.74) | 92.98 (92.98) | 93.00 | - | 96.31 |
| Vehicle | 81.78 (88.65) | **85.26** (87.99) | 85.06 (86.61) | 84.47 (85.04) | 53.00 | 79.53 | 78.45 |
| Ionos-phere | 91.93 (94.15) | 86.50 (94.29) | 87.45 (92.38) | 89.52 (93.33) | - | **92.12** | - |
| PID | **74.26** (79.69) | - | - | - | 74.00 | - | - |
| Zoo | **95.71** (98.74) | 95.62 (97.14) | 95.64 (97.14) | - | - | - | - |
| Hill-valley | 56.25 (57.64) | **57.78** (60.71) | 57.68 (61.26) | 57.61 (60.44) | - | 54.13 | - |

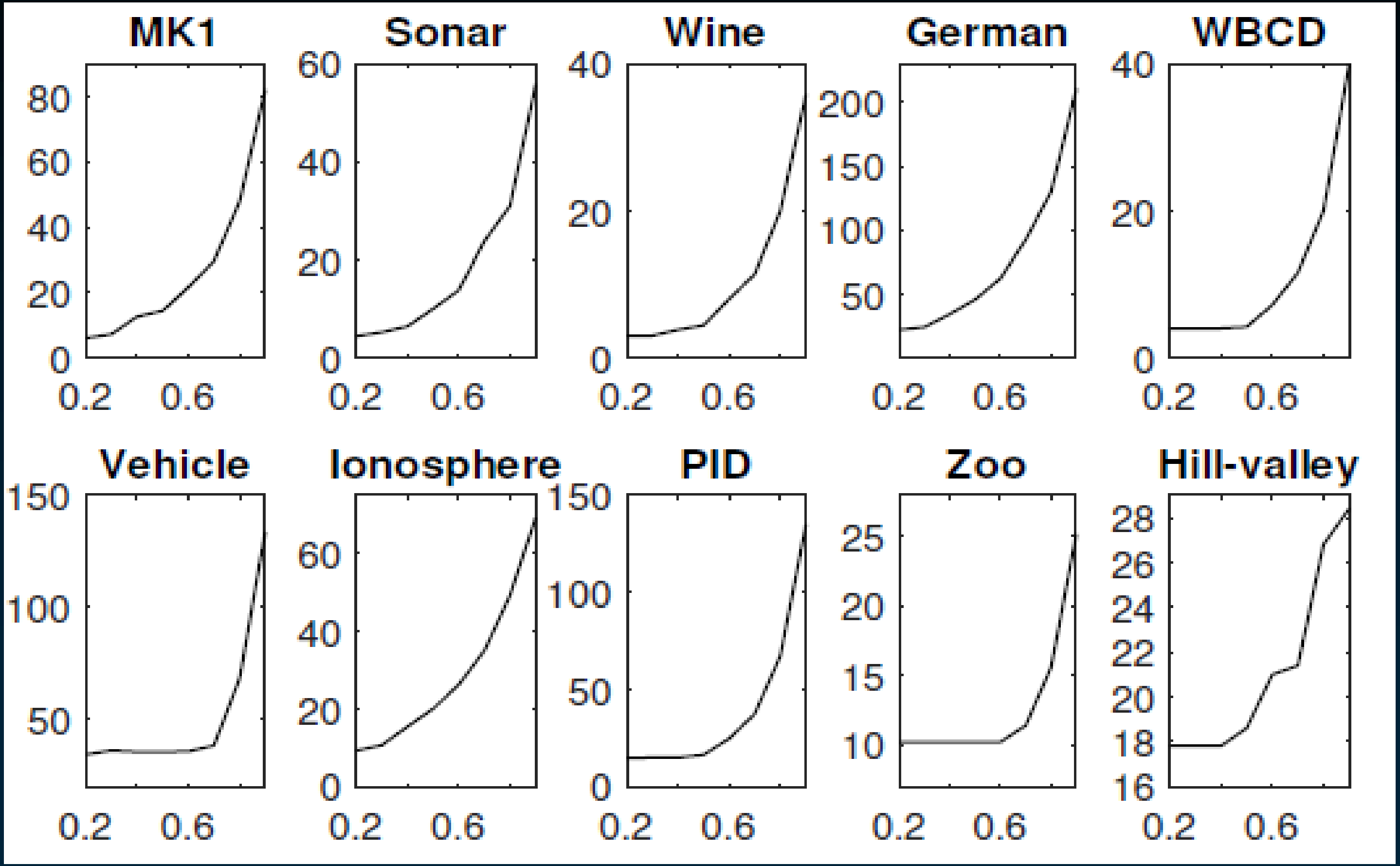
# Average number of selected features

| Data set | FAM-BSO | PSO(3-1) [43] | PSO(4-1) [43] | BPSO-2Stage [57] | U-FAM [27] | ACO-ER [1] | GP$mtfs$ [32] |
|---|---|---|---|---|---|---|---|
| MK1 | 83.34 | 107.14 | 83.54 | **80.72** | - | 83.03 | - |
| Sonar | 29.85 | 31.76 | 11.3 | - | 36.00 | - | **9.45** |
| Wine | 6.41 | 9.44 | 8.1 | 5.1 | 11.01 | - | **4.08** |
| German | 12.03 | 16.82 | 13.68 | **8.62** | - | 10.76 | - |
| WBCD | 14.84 | 19.06 | 8.12 | **6.68** | 17.01 | - | 6.72 |
| Vehicle | 9.03 | 10.58 | 9.54 | 7.3 | 9.00 | 9.86 | **5.37** |
| Ionosphere | 17.05 | 18.38 | **3.26** | 8.9 | - | 12 | - |
| PID | **4.01** | - | - | - | 7.00 | - | - |
| Zoo | 8.42 | 9.96 | **7.98** | - | - | - | - |
| Hill-valley | 48.34 | 60.65 | **13.16** | 37.1 | - | 47.63 | - |

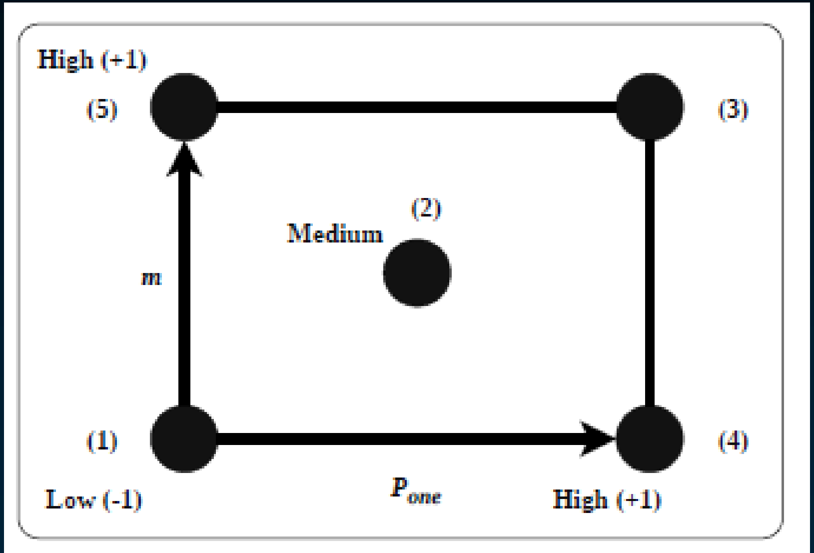
# Accuracy rates with different vigilance value



# Number of generated prototype nodes (hidden nodes)



# Real-world case study (Human motion detection)




| Experiment # | Noise-free (std. dev.) | Noisy (std. dev.) |
|---|---|---|
| Experiment 1 ($m$=3, and $P_{one}$=0) | 0.0154 (1.4e-3) | 0.0616 (10.7e-3) |
| Experiment 2 ($m$=5, and $P_{one}$=0.5) | 0.0246 (8.8e-3) | 0.0669 (13.5e-3) |
| Experiment 3 ($m$=7, and $P_{one}$=1) | 0.0112 (5.7e-3) | 0.0613 (8.8e-3) |
| Experiment 4 ($m$=3, and $P_{one}$=1) | 0.0236 (17.9e-3) | 0.0658 (9.5e-3) |
| Experiment 5 ($m$=7, and $P_{one}$=0) | **0.0098** (2.4e-3) | **0.0574** (6.8e-3) |

# Under review manuscript

- **Pourpanah, F.,** Shi, Y., Lim, C. P., Hao, Q., Tan, C. J., Feature selection based on brain storm optimization for data classification. *Applied Soft Computing,* Manuscript ID: ASOC-D-18-00890R1

# Problems

- FAM:
  - To avoid the problem of category proliferation, FAM converts an *M*-dimensional input sample into *2M*-dimensional. Thus search space becomes more complex and requires longer execution time.

To overcome this solution Fuzzy Min-Max (FMM) can be used.

- *BSO:*
  - Uses distance *k*-means clustering to categorize solutions into *m* groups, which takes long execution to measure the distance.

Objective space solutions can be used

# Accuracy rates

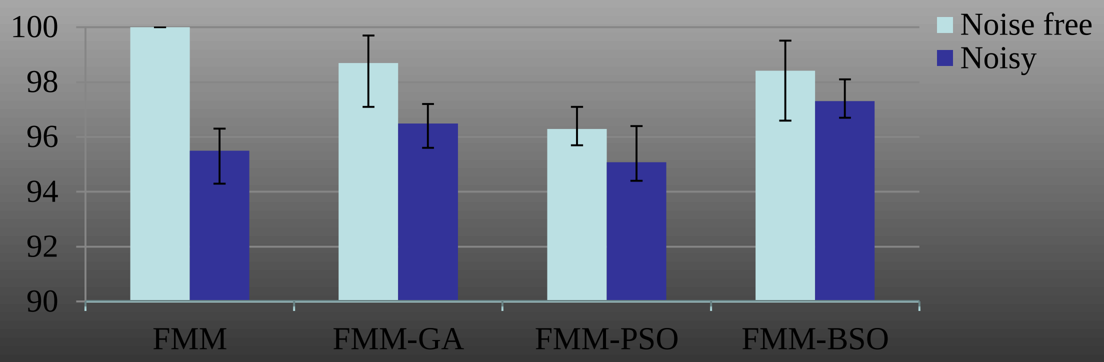
| Data sets | PSO | GA | SA | ALO | BBA | CS | ACBFO | ISEDBFO | FMM-BSO | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | Lower | Mean | Upper |
| **Australian** | 85.5 | 86.1 | 86.2 | 86.1 | 86.5 | 85.4 | 86.9 | **87.3** | 72.56 | 73.46 | 75.37 |
| **Bupa liver** | 71.1 | 70.1 | 72.3 | 71.2 | 69.2 | 68.9 | 74.2 | **74.8** | 69.30 | 70.90 | 71.70 |
| **Cleveland heart** | 84.1 | 82.4 | 84.2 | 82.5 | 82.5 | 84.1 | 85.8 | **86.1** | 83.40 | 85.17 | 87.38 |
| **Diabetes** | 76.2 | 77.1 | 77.3 | 76.5 | 77.5 | 77.3 | 77.9 | 77.6 | 80.74 | **82.24** | 85.65 |
| **German** | 74.4 | 75.7 | 76.7 | 75.5 | 76.2 | 76.7 | 76.8 | 77.4 | 88.78 | **89.83** | 90.53 |
| **Ionosphere** | 94.8 | 95.3 | 93.7 | 94.1 | 95.9 | 92.8 | 96.2 | **96.6** | 88.84 | 89.59 | 90.98 |
| **Sonar** | 85.2 | 87.1 | 85.8 | 88.8 | 90.2 | 89.7 | **93.5** | 92.8 | 88.90 | 89.93 | 91.19 |
| **Vowel** | 57.2 | 59.6 | 58.3 | 61.6 | 64.8 | 63.9 | 64.9 | 66.6 | 91.84 | **92.52** | 93.09 |
| **Thyroid** | 95.1 | 95.1 | 95.2 | 95.5 | 94.2 | 95.9 | 96.3 | **97.2** | 94.06 | 94.72 | 95.76 |
| **Yeast** | 56.5 | 57.3 | 57.4 | 61.4 | 60.3 | 62.7 | 63.3 | 65.3 | 67.43 | **69.46** | 72.34 |
| **Mean** | 78.0 | 78.6 | 78.7 | 79.3 | 79.7 | 79.7 | 81.6 | 82.2 | 82.6 | **83.8** | 85.4 |

# Average number of selected features

| Data sets | PSO | GA | SA | ALO | BBA | CS | ACBFO | ISEDBFO | FMM-BSO |
|---|---|---|---|---|---|---|---|---|---|
| **Australian** | 9.8 | 9.0 | 9.7 | 9.3 | 10.1 | 9.5 | 8.6 | 8.2 | **3.7** |
| **Bupa liver** | 5.9 | 5.8 | 5.6 | 5.8 | 5.7 | 5.6 | 5.5 | 5.4 | **3.6** |
| **Cleveland heart** | 8.5 | 8.7 | 9.2 | 8.1 | 7.9 | 8.3 | 7.2 | 6.9 | **6.2** |
| **Diabetes** | 6.3 | 6.6 | 5.5 | 5.1 | 4.8 | 5.4 | **4.2** | 4.6 | 5.1 |
| **German** | 16.8 | 15.7 | 14.3 | 13.9 | 15.2 | 14.8 | 13.1 | **12.3** | 14.3 |
| **Ionosphere** | 19.2 | 19.5 | 18.9 | 17.3 | 18.2 | 17.8 | 16.8 | 16.1 | **11.9** |
| **Sonar** | 29.4 | 27.7 | 28.4 | 28.1 | 30.0 | 27.2 | 26.1 | 25.4 | **18.0** |
| **Vowel** | 9.2 | 8.8 | 8.0 | 7.4 | 8.1 | 7.8 | 6.9 | **6.5** | 9.5 |
| **Thyroid** | 4.1 | 4.3 | 3.4 | 4.0 | 3.6 | 3.7 | **2.8** | 3.0 | 3.7 |
| **Yeast** | 6.6 | 5.7 | 6.2 | 5.0 | 5.3 | 5.1 | 4.8 | **4.6** | **4.6** |
| **Mean** | 11.6 | 11.2 | 10.9 | 10.4 | 10.9 | 10.5 | 9.6 | 9.3 | **8.1** |

# Real-world case study (motor fault detection )

| Experiment | Noise-free | | | Noisy | | |
|---|---|---|---|---|---|---|
| | Lower | Mean | Upper | Lower | Mean | Upper |
| **Exp. 1 (m=3, $P_{one}$=0 )** | 95.00 | 95.91 | 97.40 | 93.86 | 95.58 | 96.30 |
| **Exp. 2 (m=5, $P_{one}$=0.5 )** | 93.50 | 94.51 | 95.60 | 90.80 | 92.30 | 94.60 |
| **Exp. 3 (m=7, $P_{one}$=1 )** | 91.80 | 93.89 | 95.10 | 90.60 | 92.80 | 94.54 |
| **Exp. 4 (m=3, $P_{one}$=1 )** | 93.50 | 94.20 | 94.70 | 91.45 | 93.24 | 94.53 |
| **Exp. 5 (m=7, $P_{one}$=0 )** | 96.90 | **97.49** | 98.10 | 94.90 | **96.67** | 97.28 |



# Future research plan

- Mainly will focus on machine learning and feature selection:
  - Proposing binary BSO (BBSO) for feature selection and classification
  - Adopting the structure of the proposed BBSO to tackle high-dimensional problems
  - Working on imbalance classification problems (with Salim)

- Publication plan
  - A hybrid model of fuzzy min-max and brain storm optimization for feature selection and data classification (Neurocomputing)
  - Deep learning for unmanned aerial vehicles: A comprehensive survey (IEEE Access )
  - Binary brain storm optimization in objective space for feature selection ( IEEE CEC 2019)

# Thank you