DATA FUSION: PROBABILISTIC AND DS BASED

BAYES THEORY

2 Statement of Bayes' theorem

Bayes' theorem relates the conditional and marginal probabilities of stochastic events A and B:

$P(A|B) = \frac{P(B|A)\,P(A)}{P(B)}$.

Each term in Bayes' theorem has a conventional name:

- P(A) is the prior probability or marginal probability of A. It is "prior" in the sense that it does not take into account any information about B.
- $P(A|B)$ is the conditional probability of A, given B. It is also called the posterior probability because it is derived from or depends upon the specified value of B.
- $P(B|A)$ is the conditional probability of B given A.
- P(B) is the prior or marginal probability of B, and acts as a normalizing constant.

BAYESIAN SENSORS

2.3.1 Bayesian Method

Let us define $p(A)$ as the probability of occurrence of an event A, and $p(A, B)$ as the probability of occurrence of two events A and B. Then, the conditional probability of occurrence of A, given that the event B has already occurred, can be related as follows:

$$p(A,\ B) = p(A \mid B)\ p(B)$$

We will also notice that because $p(A, B) = p(B, A)$,

$$p(B,\ A) = p(B \mid A)\ p(A)$$

$$p(A \mid B) = p(B \mid A)\ p(A)/p(B)$$

The above relation can also be written as follows:

$$p(A \mid B) = \frac{p(B \mid A)\ p(A)}{\sum_i p(B \mid A_i)\, p(A_i)} \tag{2.25}$$

The denominator acts as a normalization factor if there are several events of A that can be distinguished from B in a few ways. The above equation is known as Bayes' rule. Replacing A with x and B with z, we obtain the following relation:

$$p(x \mid z) = \frac{p(z \mid x)\ p(x)}{\sum_i p(z \mid x_i)\, p(x_i)} \tag{2.26}$$

EXAMPLE OF TWO BAYESIAN SENSORS

Each sensor is assumed to have made an observation and processed these data to estimate the type of the aircraft (or any moving body) using some tracking algorithm based on the current measurement and the previous measurements [24]. Hence, some prior probabilities are listed below. We assume that for sensor 1, the new set Z_1^1 is obtained from the current measurement z_1^1 and the old dataset Z_0^1, and for sensor 2, the new set Z_1^2 is obtained from the current measurement z_1^2 and the old dataset Z_0^2. Essentially, at the fusion node, the probability of x (a particular aircraft) being one of the three aircraft types is to be computed based on the latest set of data: $p\left(x \mid Z_1^1 Z_1^2\right)$. Using Bayes' rule, we obtain the following relationship [24]:

$$p\left(x \mid Z_1^1 Z_1^2\right) = p\left(x \mid z_1^1 z_1^2 Z_0^1 Z_0^2\right)$$
$$= \frac{p\left(z_1^1 z_1^2 \mid x, Z_0^1 Z_0^2\right) p\left(x \mid Z_0^1 Z_0^2\right)}{p\left(z_1^1 z_1^2 \mid Z_0^1 Z_0^2\right)} \tag{2.34}$$

Because the sensor measurements are assumed independent, we obtain

$$p\left(x \mid Z_1^1 Z_1^2\right) = \frac{p\left(z_1^1 \mid x, Z_0^1\right) p\left(z_1^2 \mid x, Z_0^2\right) p\left(x \mid Z_0^1 Z_0^2\right)}{p\left(z_1^1 z_1^2 \mid Z_0^1 Z_0^2\right)} \tag{2.35}$$

BAYES FUSION

On the basis of the Equation 2.35, we derive the equation

$$p\left(x \mid Z_1^1 Z_1^2\right) = \frac{p\left(x \mid Z_1^1\right) p\left(z_1^1 \mid Z_0^1\right) p\left(x \mid Z_1^2\right) p\left(z_1^2 \mid Z_0^2\right) p\left(x \mid Z_0^1 Z_0^2\right)}{p\left(x \mid Z_0^1\right) p\left(x \mid Z_0^2\right) p\left(z_1^1 z_1^2 \mid Z_0^1 Z_0^2\right)} \quad (2.36)$$

Finally, at the fusion node, the posterior probability for the aircraft x is given as follows [24]:

$$p\left(x \mid Z_1^1 Z_1^2\right) = \frac{p\left(x \mid Z_1^1\right) p\left(x \mid Z_1^2\right) p\left(x \mid Z_0^1 Z_0^2\right)}{p\left(x \mid Z_0^1\right) p\left(x \mid Z_0^2\right)} \quad (2.37)$$

times the normalization factor.

Thus, Equation 2.37 yields the required fusion solution using the Bayesian approach.

EXAMPLE

Let us assume that two sensors are observing an aircraft [24]. From the signature of the aircraft, it could be either one of the three aircraft: (1) Learjet (LJ) (the jet-powered Bombardier), (2) Dassault Falcon (DF), or (3) Cessna (CC; the propeller-driven Cessna Caravan). The probability values are given in Table 2.1 [24]. The next step is to calculate the fused probabilities for the latest data. The computed values of 0.5, 0.4, and 0.1 (at the fusion node, in Table 2.1) could be the prior estimates of what the aircraft could reasonably be (or they could be based on a previous iteration using the old data). Now, using the values from Table 2.1, we can compute the fused probabilities at the fusion center as follows:

1) $p\left(x=\mathrm{LJ} \mid Z_1^1 Z_1^2\right) \approx \dfrac{0.7 * 0.80 * 0.5}{0.4 * 0.6} = 1.1667$

2) $p\left(x=\mathrm{DF} \mid Z_1^1 Z_1^2\right) \approx \dfrac{0.29 * 0.15 * 0.4}{0.4 * 0.3} = 0.145$

3) $p\left(x=\mathrm{CC} \mid Z_1^1 Z_1^2\right) \approx \dfrac{0.01 * 0.05 * 0.1}{0.2 * 0.1} = 0.0025$

TABLE 2.1

Dataset from Two Sensors (Example 2.1)

Sensor 1	Sensor 2
Posterior probabilities (from the previous iteration)	
$p\left(x=\mathrm{LJ} \mid Z_0^1\right)=0.4$	$p\left(x=\mathrm{LJ} \mid Z_0^2\right)=0.6$
$p\left(x=\mathrm{DF} \mid Z_0^1\right)=0.4$	$p\left(x=\mathrm{DF} \mid Z_0^2\right)=0.3$
$p\left(x=\mathrm{CC} \mid Z_0^1\right)=0.2$	$p\left(x=\mathrm{CC} \mid Z_0^2\right)=0.1$
The computed values at the fusion node	
$p\left(x=\mathrm{LJ} \mid Z_0^1 Z_0^2\right)=0.5$	
$p\left(x=\mathrm{DF} \mid Z_0^1 Z_0^2\right)=0.4$	
$p\left(x=\mathrm{CC} \mid Z_0^1 Z_0^2\right)=0.1$	
Updated posterior probabilities	
$p\left(x=\mathrm{LJ} \mid Z_1^1\right)=0.7$	$p\left(x=\mathrm{LJ} \mid Z_1^2\right)=0.8$
$p\left(x=\mathrm{DF} \mid Z_1^1\right)=0.29$	$p\left(x=\mathrm{DF} \mid Z_1^2\right)=0.15$
$p\left(x=\mathrm{CC} \mid Z_1^1\right)=0.01$	$p\left(x=\mathrm{CC} \mid Z_1^2\right)=0.05$

Source: Challa, S., and D. Koks. 2004. *Sadhana* 29(2):145–76.

$$p\left(x \mid Z_1^1 Z_1^2\right) = \frac{p\left(x \mid Z_1^1\right) p\left(x \mid Z_1^2\right) p\left(x \mid Z_0^1 Z_0^2\right)}{p\left(x \mid Z_0^1\right) p\left(x \mid Z_0^2\right)}$$

times the normalization factor.

After the fusion of probabilities using Bayes' rule (and after including the normalization factor of 0.7611), we finally obtain the following results (based on the old probabilities and the new data):

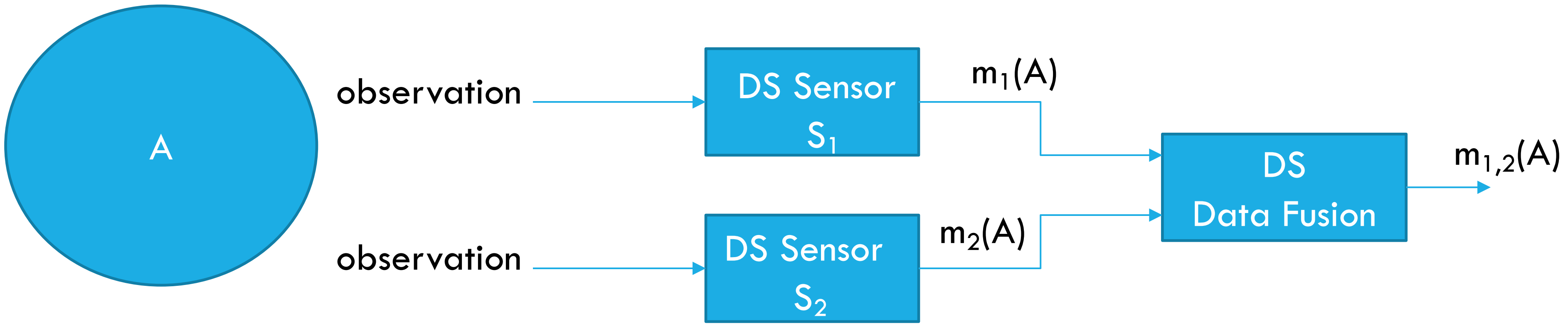
The probability that (a) the aircraft is a Learjet, $p(x = Lj)$, is 0.888, (b) the aircraft is a Falcon is 0.1104, and (c) the aircraft is a Cessna is 0.0019. From this result, we infer that the aircraft is most likely the Learjet (88.8%). The probability that it would be a Falcon is much less (11%) and, almost certainly, it would not be a Cessna (0.2%) because it has negligible posterior probability.

DEMPSTER-SHAFER DF

DEMPSTER-SHAFER THEORY

generalization of Bayesian approach "theory of evidence"

implementation via quantitative definitions of "belief" and "plausibility"



Derive degrees of belief/evidence re the states of the universe from the observations of each sensor
Use DS evidence fusion to the degrees of belief computed from each sensor to derive a fused view of the universe.

Dempster-Shafer Theory

- The Dempster–Shafer philosophy incorporates a third aspect—the “unknown.”
- In addition to the third state, this method deals with the assigned measures of “belief” (in any of these three states) in terms of “mass,” in contrast to the probabilities.
- The DS method and the Bayes’ approach both assign some weighting: either masses or probabilities.
- Masses could more or less be regarded as probabilities, but not as true probabilities in the usual sense.
- The DS method provides a rule for determining the confidence measures for the three states of knowledge, based on data from old and new evidence.
- Sensor DSDF can also be used to draw inferences about the joint distribution of two sets of random variables, keeping in mind that the measurements being corrupted with noise are themselves random variables.

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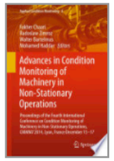

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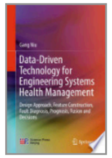

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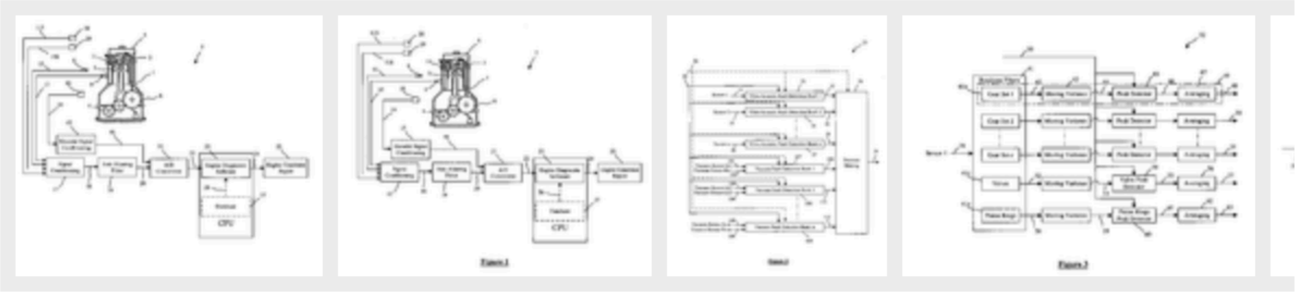
Vibro-acoustic engine diagnostic system

Abstract

A diagnostic system is used for detecting the health condition of moving internal mechanical components in internal combustion engines. The system uses measurements of engine vibration and acoustic signals during cold or hot engine test. The system includes engine vibration and acoustic sensing, engine vacuum sensing, signal conditioning and pre-filtering, analog to digital conversion, advanced digital signal processing, and decision making. Engine vibration and acoustic signals are first amplified and then passed through a low-pass filter. The signals are then digitized and sent to a computer. An engine diagnostic software receives the digitized data and performs digital filtering to isolate signal parts that most influenced by each engine moving mechanical component of interest. Features are then extracted using statistical analysis and passed to a decision making inferences. The decision making inferences utilize fuzzy logic engines to fuse feature values and reach a conclusive decision about each component condition. The system is then summarizes all results and presents them to the operator.

Images (10)



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DS SENSORS

- In a situation wherein the two sensors contribute strongly differing opinions on a given event, but agree very weakly on the third state, the DSSF model will favor the third alternative.
- In the DS method, we have to assign masses to all the subsets of the entities of the universe.
- For a universe with *n* members, there are 2*n* (that is, the power set) subsets possible when masses are assigned, say, "1" to each element within the subset and "0" to each one that is not.
- A measure of the confidence in each of the states has to be assigned
- The masses can be fused using the DS rule of combination.
- It also introduces the concepts of "support" and "plausibility."

D-S ENVIRONMENT, CONT.

Θ (Theta): $\Theta = \{\theta_1, \theta_2, \theta_3, \dots, \theta_n\}$

All the possible subset of $\theta = \{A, B, F\}$

An environment is called a *Frame of Discernment* where its elements may be interpreted as possible answers, and only one answer is correct.

D-S ENVIRONMENT, CONT.

Θ (Theta): $\Theta = \{A, B, F\}$

A set of size N has exactly 2^N subsets, including itself, and these subsets define the Power Set ($P(\Theta)$):

$$P(\Theta) = \{\emptyset, \{A\}, \{B\}, \{F\}, \{A, B\}, \{A, F\}, \{B, F\}, \{A, B, F\}\}$$

The Power Set of the environment has as its elements all answers to the possible questions of the Frame of Discernment.

MASS FUNCTIONS

In D-S Theory, the Degree of Belief in evidence is analogous to the mass of a physical object (mass of evidence supports a belief). Evidence measure ≡ amount of the mass ≡
Basic Probability Assignment (BPA).

Fundamental difference between D-S Theory and probability theory is the treatment of ignorance.

Every set in the power set of the universe which has mass value greater than 0 is considered a focal element.

- Let Ω be a finite set called a frame of discernment.
- A mass function is a function $m : 2^{\Omega} \to [0, 1]$ such that

$$\sum_{A \subseteq \Omega} m(A) = 1.$$

- The subsets A of Ω such that $m(A) \neq 0$ are called the focal sets of Ω.
- If $m(\emptyset) = 0$, m is said to be normalized (usually assumed).

NON-BELIEF VS. IGNORANCE

D-S does not force belief to be assigned to ignorance. Instead, the mass is assigned only to those subsets of the environment to which you wish to assign belief.

Not assigned belief $\equiv$ no belief or non-belief. Should be associated with the environment Θ. Disbelief $\not\equiv$ non-belief. $m_1(\{B, F\}) = 0.7$. $m_1(\Theta) = 0.3$.

Every set in the Power Set of the environment which has a mass greater than zero is a *Focal Element*.

BELIEF FUNCTION

$$Bel : 2^{\Theta} \rightarrow [0,1]$$

$$Bel(X) = \sum_{Y \subseteq X} m(Y) \qquad for\ each\ X \subseteq \Theta$$

Bel(X) : the degree of support.

To what extent does the evidence support the proposition

Properties of the belief function:

$$Bel(\Theta) = 1$$

$$Bel(X) = 0\ if\ X \not\subset \Theta$$

$$0 < Bel(X) < 1\ \ if\ X \subseteq \Theta\ and\ \ X \neq \Theta$$

$$Bel(X) = m(X)\ \ for\ each\ X \subseteq \Theta\ containing\ only\ one\ element$$

$$Bel(X) + Bel(\bar{X}) \leq 1$$

PLAUSIBILITY FUNCTION

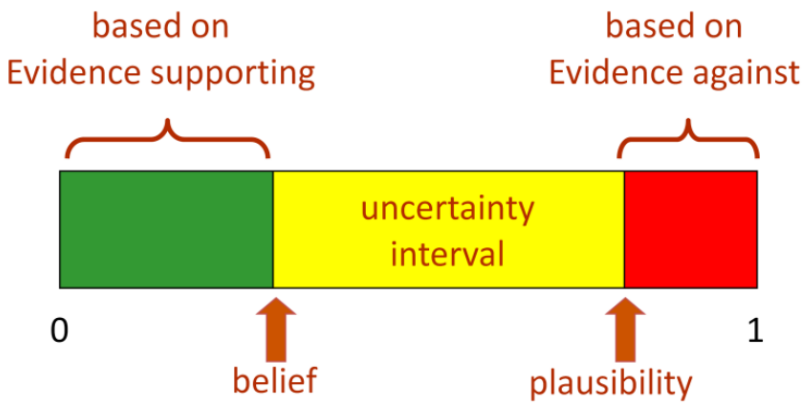
The probability that the evidence is consistent with (does not contradict) the proposition

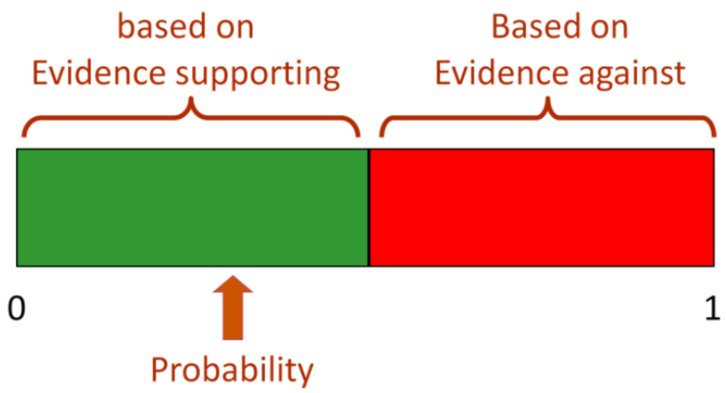
$$Pl(A) = 1 - Bel(\text{not } A)$$

The belief *Bel(A)* for a set A is defined as the sum of all the masses of subsets of the set of interest.

The upper and lower bounds of a probability interval can be defined. This interval contains the precise probability of a set of interest, and is bounded by the belief (or support) and plausibility (consistency):

$$bel(A) \leq P(A) \leq pl(A)$$





BEL() EXAMPLE

A (Airliner), B (Bomber), F (Fighter)
$m_1(\{A\}) = 0$
$m_1(\{B\}) = 0$
$m_1(\{F\}) = 0.1$
$m_1(\{A, F\}) = 0$
$m_1(\{A, B\}) = 0.7$
$m_1(\{B, F\}) = 0$
$m_1(\{A, B, F\}) = 0.2$

$$\mathrm{Bel}_1(\{A, B\}) = m_1(\{A, B\}) + m_1(\{A\}) + m_1(\{B\})$$
$$0.7 + 0 + 0 = 0.7$$

EVIDENCE

First radar data:

$$m_1(\{B, F\}) = 0.7 \qquad m_1(\Theta) = 0.3$$

Second radar data:

$$m_2(\{B\}) = 0.9 \qquad m_2(\Theta) = 0.1$$

DATA FUSION USING D-S

$$Bel(A) = \sum_{B \subseteq A} m(B)\text{, for all } A \subseteq \theta$$

$$m(A) = \sum_{B \subseteq A} (-1)^{|A-B|} Bel(B)$$

$$\text{Plausibility}_i(A \quad Q(A) = \sum_{A \subseteq B} m(B) \text{ for all } A \subseteq \theta$$

$$m_i \oplus m_j(A) = \frac{\sum_{E_k \cap E_{k'} = A} m_i(E_k) m_j(E_{k'})}{1 - \sum_{E_k \cap E_{k'} = \phi} m_i(E_k) m_j(E_{k'})}$$

$$Q(A) = \sum_{A \subseteq B} m(B) \text{ for all } A \subseteq \theta$$

COMBINATION RULE

$$m_i \oplus m_j(A) = \frac{\sum\limits_{E_k \cap E_{k'} = A} [w_i m_i(E_k) w_j m_j(E_{k'})]}{1 - \sum\limits_{E_k \cap E_{k'} = \phi} [w_i m_i(E_k) w_j m_j(E_{k'})]}$$

$$Dou(A) = Bel(\neg A)$$

and the *upper probability function* is given by

$$P^*(A) = 1 - Dou(A)$$

This expresses how much we should believe in A if all currently unknown facts were to support A.

CONFLICT IN EVIDENCE

$$K^{-1} = 1 - \sum_{X \cap Y = \phi} m_1(X) \bullet m_2(Y) = \sum_{X \cap Y \neq \phi} m_1(X) \bullet m_2(Y)$$

when $A \neq \varnothing$. The function m is a basic probability assignment if $K^{-1} \neq 0$; if $K^{-1}=0$ then $m_1 \oplus m_2$ does not exist and m_1 and m_2 are said to be *totally* or *flatly contradictory*.

The quantity Log K = Con(Bel_1,Bel_2) is called the *weight of conflict* between Bel_1 and Bel_2.

$\theta = \{D, D'\}$

$m_1(\{D\})=0.8$	$m_2(\{D\})=0.9$
$m_1(\{D'\})=0$	$m_2(\{D'\})=0$
$m_1(\{D, D'\})=0.2$	$m_2(\{D, D'\})=0.1$

D-S

$m_1(\{D\})=0.8$ $\quad$ $m_2(\{D\})=0.9$

$m_1(\{D'\})=0$ $\quad$ $m_2(\{D'\})=0$

$m_1(\{D, D'\})=0.2$ $\quad$ $m_2(\{D, D'\})=0.1$

The solution can be more clearly illustrated if a table is created with rows and columns named by subsets of θ:

		m_2		
		{D}: 0.9	{D'}: 0	{D, D'}: 0.1
m_1	{D}: 0.8	0.72	0	0.08
	{D'}: 0	0	0	0
	{D, D'}: 0.2	0.18	0	0.02

Firstly K is calculated. By definition

$$K^{-1} = 1 - \sum_{X \cap Y = \phi} m_1(X) \bullet m_2(Y)$$

$$= 1 - (0 + 0)$$

COMBINING EVIDENCE

For each probability we want to combine the following formula is used:

$$m(A) = K \sum_{X \cap Y = A} m_1(X) \bullet m_2(Y)$$

Therefore:

$m_1 \oplus m_2(\{D\}) = (1)\,(0.72 + 0.08 + 0.18) = 0.98$
$m_1 \oplus m_2(\{D'\}) = (1)\,(0) = 0$
$m_1 \oplus m_2(\{D, D'\}) = (1)\,(0.02) = 0.02$

So given the evidence presented by m_1 and m_2, we can state that the most probable belief for this universe of discourse is D.

We can also state that the weight of conflict between m_1 and m_2 is Log 1 = 0. Therefore the evidence given by m_1 and m_2 does not contradict.

Classification Example

Consider a universe of four illnesses

- All: allergy
- Flu : flu
- Cold: cold
- Pneu : pneumonia

Θ={ All, Flu, Cold,Penu}.

When we begin, with no information m is:

{Θ} (1.0)

Suppose m_1, corresponds to our belief after observing fever:

{Flu, Cold, Pneu } is (0.6)

{Θ} is (0.4)

Suppose m_2, corresponds to our belief after observing a runny nose:

{All, Flu, Cold} is (0.8)

(Θ) is (0.2)

Evidence accumulation

Let All be A
Flu be F
Cold be C
Penu be P
Thus, Θ={A,F,C,P}

We have the following assessments:

m_2

	{A,F,C} is 0.8	Θ is 0.2
{F,C,P} is 0.6	{F,C} is 0.8*0.6=0.48	{F,C,P} is 0.6*0.2=0.12
Θ is 0.4	{A,F,C} is 0.4*0.8=0.32	Θ is 0.2*0.4=0.08

m_1

Intersection of Θ in m_2 with {F,C,P} in m_1

We can combine m_1 and m_2:

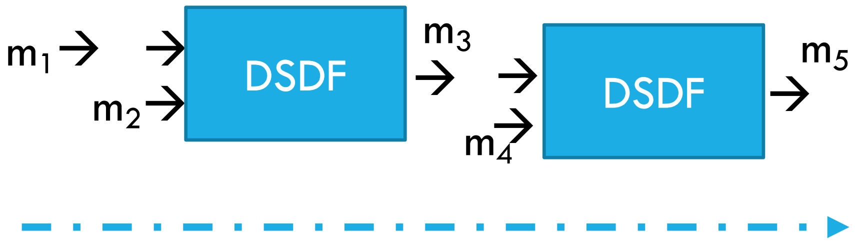
Intersection of {F,C,P} in source m_1 with {A,F,C} in source m_2

Therefore, our updated assessment based on the combination of the two pieces of evidence, call it m_3 is:
{Flu,Cold} is 0.48; {all,Flu,Cold} is 0.32; {Flu, Cold, Penu} is 0.12, Θ is 0.08

Suppose m_4 corresponds to a new evidence that the problem goes away on trips and thus is associated with allergy:

{All} is 0.9

{Θ} is) is 0.1



m_4

		{A} is 0.9	Θ is 0.1
m_3	{F,C,} is 0.48 {A,F,C} is 0.32 {F,C,P} is 0.12	{Φ} is 0.432 {A} is 0.288 {Φ} is 0.108	{F,C} is 0.048 {A,F,C} is 0.032 {F,C,P} is 0.012
	Θ is 0.08	{A} is 0.072	Θ is 0.008

If we allocate 0.54 (which is 0.432+0.108} to the {Φ} we are left with 0.46 for the focal elements: Call it, m_5:

{Flu,Cold} is 0.048/0.46= 0.104
{Allergy, Flu, Cold} is 0.032/0.46=0.0696
{Flu, Cold, Penu} is (0.012)/0.46= 0.0261
{Allergy} is (0.288+0.072}/0.46= 0.783
{Θ} is 0.008/0.46= 0.017

What is the belief, plausibility of the Allergy?

EXAMPLE 2 SENSORS THRE OBJECTS

Two sensors three objects {A: airliner, B bomber, Fighter}:

P1(Θ) = {{A,B}=0.7,{A,B,F}=0.3}, P2(Θ) = {{B}=0.9,{A,B,F}=0.1}

	$m_2(\{B\}) = 0.9$	$m_2(\Theta) = 0.1$
$m_1(\{A,B\}) = 0.7$	$\{B\}\ 0.63$	$\{A,B\}\ 0.07$
$m_1(\Theta) = 0.3$	$\{B\}\ 0.27$	$\Theta\ 0.03$

Bomber $m_3(\{B\}) = m_1(\{A,B\}) * m_2(\{B\}) + m_1(\{B\}) * m_2(\{B\}) = 0.63 + 0.27 = 0.90$
Airliner or Bomber $m_3(\{A,B\}) = m_1(\{A,B\}) * m_2(\{A,B,F\}) = 0.07$
Non-belief (No Info) $m_3(\{A,B,F\}) = m_1(\{A,B,F\}) * m_2(\{A,B,F\}) = 0.03$

EVIDENCE CONFLICT

Suppose a third sensor is provided:

$$m_3(\{F\}) = 0.95, m_3(\{A,B,F\}) = 0.05$$

	$\boldsymbol{m_1 \oplus m_2(\{B\})}$ **0.90**	$\boldsymbol{m_1 \oplus m_2(\{A,B\})}$ **0.07**	$\boldsymbol{m_1 \oplus m_2(A,B,F)}$ **0.03**
$m_3(\{F\}) = 0.95$	$\emptyset$ 0	$\emptyset$ 0	$\{F\}$ 0.0285
$m_3(A,B,F) = 0.05$	$\{B\}$ 0.045	$\{A,B\}$ 0.0035	$\{A,B,F\}$0.0015

$$m_1 \oplus m_2 \oplus m_3(\{F\}) = 0.0285$$
$$m_1 \oplus m_2 \oplus m_3(\{B\}) = 0.0450$$
$$m_1 \oplus m_2 \oplus m_3(\{A,B\}) = 0.0035$$
$$m_1 \oplus m_2 \oplus m_3(A,B,F) = 0.0015$$
$$m_1 \oplus m_2 \oplus m_3(\{\emptyset\}) = 0.0000$$

$$SUM \quad = 0.0785 \neq 1 \text{ !!!}$$

NORMALIZATION

$$m_i \oplus m_j(A) = \frac{\sum_{E_k \cap E_{k'} = A} [w_i m_i(E_k) w_j m_j(E_{k'})]}{1 - \sum_{E_k \cap E_{k'} = \phi} [w_i m_i(E_k) w_j m_j(E_{k'})]}$$

Divide each element by $1\text{-}k$ where k is defined for any set X and Y as:

$$k = \sum_{X \cap Y = \emptyset} m_1(X) m_2(Y)$$

$$k = 0.95 \times 0.90 + 0.95 \times 0.07$$
$$k = 0.8550 + 0.0665 = 0.9215$$
$$1 - k = 1 - 0.9215 = 0.0785$$

	$m_1 \oplus m_2(\{B\})$ 0.90	$m_1 \oplus m_2(\{A, B\})$ 0.07	$m_1 \oplus m_2(A, B, F)$ 0.03
$m_3(\{F\}) = 0.95$	$\emptyset$ 0	$\emptyset$ 0	$\{F\}$ 0.0285
$m_3(A, B, F) = 0.05$	$\{B\}$ 0.045	$\{A, B\}$ 0.0035	$\{A, B, F\}$ 0.0015

$$m_1 \oplus m_2 \oplus m_3(\{F\}) = \frac{0.0285}{0.0785} = 0.363$$

$$m_1 \oplus m_2 \oplus m_3(\{B\}) = \frac{0.0450}{0.0785} = 0.573$$

$$m_1 \oplus m_2 \oplus m_3(\{A, B\}) = \frac{0.0035}{0.0785} = 0.045$$

$$m_1 \oplus m_2 \oplus m_3(\{A, B, F\}) = \frac{0.0015}{0.0785} = 0.019$$

$$m_1 \oplus m_2 \oplus m_3(\{\emptyset\}) = \frac{0.0000}{0.0785} = 0.000$$

$$= 1.000$$

THREE OR MORE SENSORS

In the case of three or more sensors, Dempster's rule might in principle be applied in different ways depending on which order is chosen for the sensors. But it turns out that because the rule is only concerned with set intersections, the fusion order becomes irrelevant.

$$m^{1,2,3}(D) = \frac{\sum_{A\cap B\cap C=D} m^1(A)m^2(B)m^3(C)}{\sum_{A\cap B\cap C\neq\emptyset} m^1(A)m^2(B)m^3(C)} = \frac{\sum_{A\cap B\cap C=D} m^1(A)m^2(B)\, m^3(C)}{1-\sum_{A\cap B\cap C=\emptyset} m^1(A)m^2(B)m^3(C)},$$

EXAMPLE

Target Type	Sensor 1 Mass m^1	Sensor 2 Mass m^2	Sensor 3 Mass m^3
A	0.2	0.2	0
B	0	0	0.2
C	0.3	0	0
A,C	0	0.3	0
B,C	0	0	0.2
A,B,C,D	0.5	0.5	0.6
(Total mass)	1	1	1

COMBINING SENSOR 1 AND 2 AND THEN COMBINE SENSOR 3.

For sensor 1 and 2

Conflicting Factor K = $m^1(C)m^2(A)$ = $0.3*0.2$ = 0.06, 1−K = 0.94

$$m^{1,2}(A) = (m^1(A)m^2(A) + m^1(A)m^2(A,C) + m^1(A)m^2(A,B,C,D) + m^1(A,B,C,D)m^2(A))/0.94$$

$$= (0.2*0.2 + 0.2*0.3 + 0.2*0.5 + 0.5*0.2)/0.94 = 0.31915$$

$$m^{1,2}(C) = \frac{m^1(C)m^2(A,C)+m^1(C)m^2(NoInfo)}{0.94} = (0.3*0.3 + 0.3*0.5)/0.94 = 0.25532$$

$$m^{1,2}(A,C) = \frac{m^1(NoInfo)m^2(A,C)}{0.94} = \frac{0.5*0.3}{0.94} = 0.15957$$

$$m^{1,2}(A,B,C,D) = \frac{m^1(A,B,C,D)m^2(A,B,C,D)}{0.94} = \frac{0.5*0.5}{0.94} = 0.26596$$

SENSOR 1 AND 2 FUSED MASS

Target Type	Sensor 1 Mass m^1	Sensor 2 Mass m^2	Fused Mass Mass $m^{1,2}$
A	0.2	0.2	0.31915
C	0.3	0	0.25532
A,C	0	0.3	0.15957
A,B,C,D	0.5	0.5	0.26596
(Total mass)	1	1	1

We notice the fused masses summation is equal to 1, and the conflicting factor is equal to 0.06 describing a great degree of accordance between sensor 1 and 2 which is obvious from the mass assignments for each one individually.

COMBINE THE RESULT WITH SENSOR3

Conflict factor = $m^{1,2}(A)m^3(B) + m^{1,2}(A)m^3(B,C) + m^{1,2}(C)m^3(B) + m^{1,2}(A,C)m^3(B)$

$= 0.31915*0.2 + 0.31915*0.2 + 0.25532*0.2 + 0.15957*0.2 = 0.21064$

$$m^{1,2,3}(A) = \frac{m^{1,2}(A)m^3(A,B,C,D)}{0.78936} = \frac{0.31915*0.6}{0.78936} = 0.2426$$

$$m^{1,2,3}(B) = \frac{m^{1,2}(A,B,C,D)m^3(B)}{0.78936} = \frac{0.26596*0.2}{0.78936} = 0.0674$$

$$m^{1,2,3}(C) = \frac{m^{1,2}(C)m^3(B,C)+m^{1,2}(C)m^3(A,B,C,D)+m^{1,2}(A,C)m^3(B,C)}{0.78936} = \frac{0.25532*0.2+0.25532*0.6+0.15957*0.2}{0.78936} = 0.2992$$

$$m^{1,2,3}(A,C) = \frac{m^{1,2}(A,C)m^3(A,B,C,D)}{0.78936} = \frac{0.15957*0.6}{0.78936} = 0.1213$$

$$m^{1,2,3}(B,C) = \frac{m^{1,2}(A,B,C,D)m^3(B,C)}{0.78936} = \frac{0.26596*0.2}{0.78936} = 0.0674$$

$$m^{1,2,3}(A,B,C,D) = \frac{m^{1,2}(A,B,C,D)m^3(A,B,C,D)}{0.78936} = \frac{0.26596*0.6}{0.78936} = 0.2021$$

FINAL FUSION RESULT

Target Type	Sensor 1&2 Mass $m^{1,2}$	Sensor 3 Mass m^{3}	Fused Mass Mass $m^{1,2,3}$
A	0.31915	0	0.2426
B	0	0.2	0.0674
C	0.25532	0	0.2992
A,C	0.15957	0	0.1213
B,C	0	0.2	0.0674
A,B,C,D	0.26596	0.6	0.2021
(Total mass)	1	1	1

ANOTHER EXAMPLE: TWO DS SENSORS

Consider Example 2.1. Here, instead of the prior probabilities, we use the masses shown in Table 2.2 [24]. Computing the fused mass for the possible states using the DS fusion rule, the values of the masses obtained are presented in Table 2.2. The computation is illustrated for the state that the aircraft Learjet (LJ) occurs, meaning that, in Equation 2.39, the variable C = Learjet aircraft. All other results are shown in Table 2.2. Here, it is assumed that there is a possible state of "fast," being the aircraft LL and DF, and the unknown state, being the aircraft LJ, DF, and CC. Hence, we obtain the following result [24]:

$$
\begin{aligned}
m^{1,2}(\mathrm{LJ}) \propto\ & m^1(\mathrm{LJ})m^2(\mathrm{LJ}) + m^1(\mathrm{LJ})m^2(\mathrm{LJ},\mathrm{DF}) + m^1(\mathrm{LJ})m^2(\mathrm{LJ},\mathrm{DF},\mathrm{CC}) \\
& + m^1(\mathrm{LJ},\mathrm{DF})m^2(\mathrm{LJ}) + m^1(\mathrm{LJ},\mathrm{DF},\mathrm{CC})m^2(\mathrm{LJ}) \\
=\ & 0.3 * 0.4 + 0.3 * 0.45 + 0.3 * 0.03 + 0.42 * 0.4 + 0.1 * 0.4 \\
=\ & 0.47
\end{aligned}
$$

From the results, it can be inferred that the aircraft is possibly a Learjet, as its final mass is 0.55 (55%). The "fast" state's fused mass is 0.29 (29%), which shows that the aircraft would certainly not be the Cessna (CC), because it has a fused mass of only 0.4%.

TWO DS SENSORS

TABLE 2.2

Masses Assigned for Each Sensor for the Computation of DS Rule

State in the Power Set	Sensor 1 Mass = m^1	Sensor 2 Mass = m^2	DS-Fused Final Masses for Each State (after the Application of the DS-Fusion Rule and the Normalization Factor)
Learjet (LJ)	0.30	0.40	0.55
Falcon (DF)	0.15	0.10	0.16
Caravan (CC)	0.03	0.02	0.004
Fast (LJ, DF)	0.42	0.45	0.29
Unknown (LJ, DK, CC)	0.10	0.03	0.003
Total mass	1.00	1.00	1.007

Source: Challa, S., and D. Koks. 2004. *Sadhana* 29(2):145–76.

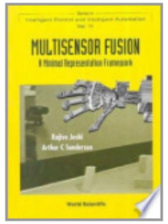
DS AND BAYES FUSION: COMPARISON

- The Bayesian inference method (BIM) uses probability theory and hence does not have a third state called “unknown.”
- The probability itself is based on the occurrence of an event when numerous experiments are carried out. It is based on only two states, and there is an element of chance involved in BIM.
- In contrast, the DS theory considers a space of elements that reflect the state of our knowledge after making a measurement.
- In the BIM method, there is no “unknown” state; either an event has occurred or not, or either an event A or an alternative event B has occurred.
- In the DS model, the state “unknown” could be the state of our knowledge at any time about an object, but we are not sure.
- DS *Concepts and Theory of Data Fusion requires* the masses to be assigned in a meaningful way to all the states, whereas BIM requires the priors (probabilities) to be assigned.
- However, a preliminary assignment of masses could be required to reflect the initial knowledge of the system.
- The DS model allows computation of support and plausibility, in addition to involving more computations compared to the BIM model.

ENTROPY-BASED SENSOR DATA FUSION APPROACH

- It is important for a sensor NW to perform efficiently in certain difficult environments.
- The NW should process available information efficiently and share it such that decision accuracies are enhanced.
- One interesting approach is to measure the value of information (VOI) obtained from the various sensors, and to then fuse the information if the value (a gain involving significant importance and appreciation) is added in terms of the decision accuracy (DA).
- The concept is based on the information- theoretic (metric entropy) measure and related concepts.
- The DF here is conditioned upon whether the VOI has improved the DA. .
- This is a useful process for merging similar-sensor and multisensor images to enhance the information.
- For this purpose, a metric system based on entropy can be useful.
- Entropy perceives information as a frequency of change in the information source (the digital numbers). .
- In fact, when a new set of data is added and used for analysis and inferences, then the new entropy (uncertainty) will be reduced compared to the old entropy (uncertainty), and the difference will be the gain in the information.
- The use of entropy must be viewed in this context.

BASIR DSF: EXAMPLE.



0 Eleştiriler

Eleştiri yazın

Multisensor Fusion: A Minimal Representation Framework

Yazar: Rajive Joshi, Arthur C. Sanderson

38 *Multisensor Data Fusion*

3.3.4 *Information Theory Methods*

Information-theoretic methods [17, 40] fuse data by searching for solutions which optimize various information measures in a multisensor system. Basir and Shen [14] utilize an *information variation* measure for modeling uncertainty and cooperation among sensors, and develop a stochastic weighting scheme, which operates recursively on a sensor team until it reaches a consensus. Mutambara [141] describes scalable decentralized estimation and control algorithms for linear and non-linear multisensor systems, using a decentralized extended *information filter*. Some widely used information-theoretic techniques are described below.

3.3.4.1 *Entropy Based Methods*

Entropy based methods methods fuse data by searching for solutions which minimize the uncertainty in a multisensor system. Zhou and Leung [217] describe a minimum entropy approach for multisensor data fusion in non-Gaussian environments. They represent the fused data in the form of the weighted sum of the multisensor outputs and use the varimax norm as the information measure. The optimum weights are obtained by maximizing the varimax norm of the fused data. The minimum entropy fusion solution only depends on the empirical distribution of the sensor data and makes no specific distribution assumptions about the sensor data. Chung and Shen [37] develop a team consensus approach based on information entropy, for fusing dependent sensory data. Manyika and Durrant-Whyte [132] describe an entropy based approach for data fusion and sensor management.

3.3.4.2 *Minimum Description Length Methods*

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INFORMATION THEORY

- In 1948, Claude Shannon applied the probabilistic concept in modeling message communications, with the proposal that a particular message is one element (possibility one) from a set of all possible messages.
- Given the finite set of the number of messages, any monotonic function of this number can be used as a measure of the information when one message is chosen from this set.
- The information is modeled as a probabilistic process.
- It is essential to know the probability of each message occurring, the intention being to isolate one message from all of the possible messages (in a set).
- Thus, the occurrence of this random event x is the probability p(x) of the message.
- The I(x) is the self-information of x, which somehow acts as the antagonous of the probability, because if the event x always occurs, then p(x) = 1, and no new information can be transferred, i.e, I(x)=0.
-

INFORMATION THEORY CONCEPTS

$$I(x) = \log \frac{1}{p(x)} = -\log\{p(x)\} \tag{2.40}$$

The above definition of information is intuitively appealing from an engineering viewpoint. The average self-information in the set of messages with N outputs will be [25]

$$I(x) = -N\,p(x_1)\,\log\{p(x_1)\} - N\,p(x_2)\log\{p(x_2)\},\ldots,N\,p(x_n)\log(\{p(x_n)\}) \tag{2.41}$$

Then, the average information per source output is represented by the following equation:

$$H = -N\sum_{i=1}^{n} p(x_i)\log\{p(x_i)\} \tag{2.42}$$

Here, H is also known as Shannon's entropy. However, in general, the value of N is set to 1, and hence we obtain the following relation using the natural logarithm:

$$H = -\sum_{i=1}^{n} p(x_i)\ln_2\{p(x_i)\} \tag{2.43}$$

INFORMATION THEORY CONCEPTS

Shannon introduced the mathematical concept of information and established a technical value and a meaning of information. From the above development, we can see that the entropy (somewhat directly related to the covariance) or uncertainty of a random variable X having a probability-density function $p(x)$ is defined as

$$H(x) = -E_x\{\log p(x)\} \tag{2.44}$$

It is the –ve expected value of the logarithm of the pdf of the random variable X. Entropy can be roughly thought of as a measure of disorder or lack of information. Now, let $H(\beta) = -E_\beta[\log p(\beta)]$, the entropy before collecting

data "z," and $p(\beta)$ the prior density function of β, a specific parameter of interest. When the data z is collected, we have the following relation:

$$H(\beta \mid z) = -E_{\beta/z}\{\log p(\beta \mid z)\} \tag{2.45}$$

The measure of the average amount of information provided or gained by the experiment with data z on the parameter β is provided by the following relationship:

$$I = H(\beta) - E_z\{H(\beta, z)\} \tag{2.46}$$

INFORMATION THEORY CONCEPTS

This is the "mean information" in z about β.

- We note that entropy implies the dispersion or covariance of the density function and, hence, the uncertainty.
- Thus, the information I is perceived as the difference between the prior uncertainty (which is generally large) and the "expected" posterior uncertainty (which is now reduced due to the new data adding some information about the parameter or variable of interest).
- This indicates that due to experimentation, collection, and the use of data z, the (posterior) uncertainty (which is expected to reduce) is reduced and, information is gained.
- Thus, the information is a nonnegative measure, and it is zero if $p(z,\beta)=p(z)*p(\beta)$; i.e., if the data are independent of the parameters, which implies that the data does not contain any information regarding that specific parameter.

MUTUAL INFORMATION

The information could be in the form of features for classification or data for detection of an object. Let $H(x)$ be the entropy of the observed event, and let z be a new event with its uncertainty (entropy) as $H(z)$. Then, we can evaluate the uncertainty of x after the event z has occurred and incorporate it to compute the new entropy:

$$H(x \mid z) = H(x, z) - H(z)$$

This conditional entropy $H(x \mid z)$ signifies the amount of uncertainty remaining about x after z has been observed or accounted for. Thus, if the uncertainty is reduced, information has been gained by observing and incorporating z, the new information. The mutual information $I(x,z)$ is a measure of the uncertainty after observing and incorporating z and can be represented as follows:

$$I(x, z) = H(x) - H(x \mid z)$$

Thus, the VOI is useful when we want to assess the information available from multiple sensors on a single node or from different sensors from neighboring nodes.

INFORMATION POOLING

For managed DF, there are a few important methods depending on how the information from various sensors is pooled and managed.
There are mainly three methods:
(1) the linear opinion pool,
(2) the independent opinion pool, and
(3) the independent likelihood pool.

The probabilistic elements are necessary for the theoretical development and analysis of the DF process and sensor-management methods.

- In this approach, the posterior probabilities from each information source are combined in a linear fashion as follows:

$$p(x \mid Z^k) = \sum_i w_i p\left(x \mid z_i^k\right)$$

Here, the weights (w) should add up to unity, and the individual weights range between 0 and 1. This means that the posteriors are evaluated for the variable to be fused, based on the corresponding measurements. The weights signify reliability, faith, or trustworthiness of the information source and are assumed known *a priori*. In the sensor-management scheme, a faulty sensor can be "weighted out" using a proper weight. The number of models is k.

INDEPENDENT OPINION POOL

Here, the observation set is assumed independent. The expression for the same is written as

$$p(x \mid Z^k) = \alpha \prod_i p\left(x \mid z_i^k\right) \tag{2.56}$$

This method is suitable if the priors (probabilities) are obtained independently according to the subjective prior information at each source.

INDEPENDENT LIKELIHOOD POOL

Here, each information source has common prior information. The representation of the independent likelihood pool (ILP) is shown below:

$$\begin{aligned}
&p\left(z_i^k \mid x\right)->\{\prod_i -> p(x \mid Z^k) \\
&\ldots \\
&p\left(z_N^k \mid x\right)->\{ \\
&p(x)->\{
\end{aligned} \tag{2.57}$$

The ILP is consistent with the Bayesian approach involving the DF updates, and more appropriate for MSDF applications if the conditional distributions of the measurements are independent.

These "information-pooling" methods can also be extended to include the reliability aspects of the sensor or data into their formulations, thereby helping with the sensor-management problem.

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signal strength. Secondly, the object signal strength adopts least squares estimation linearization and the equation of the signal strength transformation into the relative distance to calculate the object's location coordinate. Finally, the experimental results show the two-dimensional inductance plane sensor has remarkable performance.

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but there also a larger presence of searching agents.

5 Conclusions

This paper shows how an entropy-based model can be used to evaluate self-organizing properties of SI algorithms. Preliminary experiments, conducted using a flocking algorithm successfully employed for performing approximate clustering, demonstrate the presence of self-organizing characteristics differently from random search and classical flocking algorithm. However, entropy alone is not sufficient to assess the goodness of the algorithm in searching the space (i.e. performing clustering) and other measures are needed in order to verify the search is concentrated in interesting zones. Anyway, we believe that this model could be useful to better understand and control the behavior of multi-agent systems and to drive the user for choosing the appropriate parameters. Future works aim to evaluate and compare self-organization properties of other SI models, as Ants Colony Optimization, Particle Swarm Optimization, etc..

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