Self-organization Technique with a Norm Transformation Based Filtering for Sustainable Infocommunications Within CNS/ATM Systems

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Abstract. A self-organization machine learning technique for sustainable infocommunications within communications, navigation, and surveillance / air traffic management (CNS/ATM) systems is proposed in the paper. The proposed technique is based on the modification of the expectation-maximization algorithm with adding of components of Gaussian mixture model. The proposed technique allows for an unsupervised self-organization of system parameters into ranges (e.g., frequency bands and any other groups of homogenous parameters), which simplifies a general tuning of infocommunications for aeronautical purposes in dynamically changing conditions. The proposed technique uses a norm transformation filtering to restrict possible influence of outliers and anomalies in input system parameters. The feature that only observed input system parameters are required for all stages of data processing characterizes the proposed technique. Setting of initial parameters, stopping criteria for internal and external iterative machine learning processes, robustness and computational cost within the proposed technique are described and analyzed. An example of simulation of the proposed technique, which presents an unsupervised automatic clustering of the available radio spectrum recourse, is also shown in the paper.

Keywords: CNS/ATM Systems · Machine Learning · Sustainable Infocommunications

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1 Introduction

1.1 Introduction to the Problem

Communications, navigation, and surveillance/air traffic management (CNS/ATM) systems implementation and related activities take into account different issues, including environmental [1]. Currently, these issues can also be considered within a framework of the long-term global aspirational goal (LTAG) for international aviation of net-zero carbon emissions by 2050, which was adopted at the 41st ICAO Assembly [2]. In this regard, the relevant information and communication components of CNS/ATM systems can be presented and analyzed as sustainable information and communications technologies [3, 4] or sustainable infocommunications.

Sustainable infocommunications may be perceived as:

- Information and communication systems, which are directly characterized by the sustainable and environment-friendly structure or parameters, e.g., resource-oriented blockchain systems [5], low-power [6] and green communications [7].
- Information and communication systems, which aim to create more sustainable and environment-friendly infrastructure, systems or their features, e.g., climate change strategies [8, 9] and sustainable cities [10].

1.2 Motivation

Relevance of the above-mentioned aspects in sustainable infocommunications for aeronautical purposes within CNS/ATM systems in dynamically changing conditions can be caused by both the technical development of information and communication technology and the economic, social environmental development and protection. These features and trends in general were implemented in the Sustainable development organizing principle as part of it along with other problems and challenges in different areas of development of human society [11–15]. However, at this point possible influence of outliers and anomalies in sustainable infocommunications must be correctly taken into account. This motivates to design a technique for an unsupervised self-organization of system parameters (e.g., frequency bands and any other groups of homogenous parameters) for sustainable infocommunications within CNS/ATM systems, which simplifies their tuning and adaptation in dynamically changing conditions, and restricts such influence of outliers and anomalies.

1.3 Contribution

This research contributes a new self-organization machine learning (ML) technique for sustainable infocommunications within CNS/ATM systems, which also provides restriction of possible influence of outliers and anomalies in input system parameters due to a norm transformation filtering. The proposed technique is based on the modification of the expectation-maximization (EM) algorithm with adding of components of Gaussian mixture model (GMM) [16–18].

1.4 The Organization of the Paper

The paper consists of six sections. The introduction is presented by the first section. Second section includes a literature review and problem statement. A proposed self-organization technique for sustainable infocommunications within CNS/ATM systems is described in the third section. Results and discussions, and conclusions are presented in the fourth and fifth sections, relatively. Finally, a future research scope is given in the sixth section.

2 Literature Review and Problem Statement

The Sustainable development organizing principle in turn unfolds through the 17 United Nations Sustainable Development Goals (SDGs), which are also being dealt with their structural parts in the context of infocommunication systems and applications [11, 13–15]. Infocommunications can be considered within the both SDG 9 “Industry, innovation and infrastructure”, which takes into account information and communication technology, and SDG 11 “Sustainable cities and communities”, which takes into account a safe housing under the rapid growth of cities.

Sustainable, in particular, cognitive environment-friendly infocommunications, taking into account that the Dynamic Spectrum Access (DSA) and Signal to Noise Ratio (SNR) scenarios can vary widely in different cities depending on applications [19, 20], are based on the following systemic components (Fig. 1):

- Organizational component, which is responsible for interrelations with external infrastructure that aims to be sustainable and environment-friendly.
- Engineering component, which is responsible for a structure, technical parameters, features, efficiency of infocommunication system and serves to achieve the goals of the organizational component.

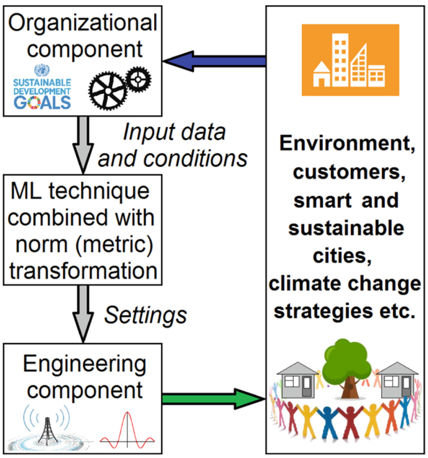

Fig. 1. Sustainable cognitive environment-friendly infocommunication system.

The paper is focused on the engineering component, which can additionally be regulated by the organizational component using the norm (metric) transformation approach [21, 22]. This approach can robustly limit the influence of outliers and anomalies that are observations in infocommunication system, which deviate so much from other observations as to arouse suspicions that they were generated by a different mechanism or appear to be inconsistent with some set of data [22–25].

The engineering component, taking into account DSA and SNR scenarios in environment-friendly cognitive radio, for modern infocommunications includes various features such as low SNR physical access, e.g., Direct Sequence Spread Spectrum and relevant spreading sequences, spatial DSA, e.g., Multiple Input Multiple Output (MIMO) and polarization antenna systems, their relevant electromagnetic field parameters etc.

Both organizational and engineering components of infocommunication system are important for sustainable development of environment-friendly air transport infrastructural parts, e.g., aircraft positioning, automatic dependent surveillance-broadcast systems, and European navigational aids network [26].

Properties and capabilities such as self-organization, self-adaptation, fault tolerance, and self-healing are promising for effective interaction between engineering and organizational components in cognitive environment-friendly infocommunications due to the possibility of autonomic precisely controlling system parameters under conditions of uncertainty [27]. These properties and capabilities can be realized effectively by means of ML and Artificial Intelligence (AI) [28] techniques, in particular neural networks, which are becoming more widespread in modern infocommunications.

The scientific problem with which the paper deals is a designing self-organization, self-adaptation and fault tolerance organizational and engineering components of sustainable environment-friendly infocommunications for aeronautical purposes. In this regard, the aim of the paper is development of self-organization technique for sustainable environment-friendly infocommunications within CNS/ATM systems, which is based on the ML approach combined with a norm (metric) transformation filtering.

3 Development of Self-organization Technique for Sustainable Infocommunications Within CNS/ATM Systems

3.1 ML Technique

Among many theoretical and practical ML approaches and techniques to the self-organization feature of a system we highlight in the paper the EM algorithm [16–18] for data clustering. The EM algorithm deals with GMM and aims to estimate their parameters and perform cluster analysis of elements within the GMM framework [18] for different purposes [15, 29].

Let $\mathbf{d} = (d_1, d_2, \ldots, d_N)^{\mathrm{T}}$ be the vector of homogenous data in an infocommunication system, where N is the amount of data. These data can be associated with parameters of infocommunication system, which are formed by the organizational component. They are also the input data for the ML self-organization technique.

The goals of cognitive part, which is based on the ML self-organization technique, are:

- Clustering of homogenous data $\mathbf{d}$ into clusters, which are subsets of parameters; this has to be done for each kind of homogenous data (e.g., the first kind of homogenous data $\mathbf{d}_1$ corresponds to spectral characteristics in DSA scenario, the second one $\mathbf{d}_2$ corresponds to energy characteristics in SNR scenario etc.).
- Clustering of heterogeneous data, which are previously clustered homogenous data sets $\mathbf{d}_k$, $k = \overline{1, K}$, where K is the number of different kinds of homogenous data in sustainable infocommunication system within CNS/ATM systems.

In the paper, we consider the achievement of the first goal, i.e. the clustering of homogenous data $\mathbf{d}$.

When using the EM algorithm, a decision on the clustering for each n-th element of homogenous data $\mathbf{d}$ to be clustered is made according to the criterion of maximum probability among posterior probabilities $\boldsymbol{\alpha} = \left(\alpha_{n,m}\right)$, $n = \overline{1, N}$, $m = \overline{1, M}$, where m is the current cluster number, M is the total number of clusters. Probabilities $\boldsymbol{\alpha}$ can be estimated at the expectation step (E-step) of the EM algorithm:

$$\alpha_{n,m} = \frac{\frac{\gamma_{\mathrm{m}}}{\sqrt{2\pi\sigma_{\mathrm{m}}^2}}\exp\left[-\frac{(d_n-\mu_{\mathrm{m}})^2}{2\sigma_{\mathrm{m}}^2}\right]}{\sum_{i=1}^{M}\frac{\gamma_i}{\sqrt{2\pi\sigma_{\mathrm{i}}^2}}\exp\left[-\frac{(d_n-\mu_{\mathrm{i}})^2}{2\sigma_{\mathrm{i}}^2}\right]},$$

where $\boldsymbol{\gamma} = (\gamma_1, \gamma_2, \ldots, \gamma_M)^{\mathrm{T}}$ is the vector of GMM weighting coefficients; $\boldsymbol{\mu} = (\mu_1, \mu_2, \ldots, \mu_M)^{\mathrm{T}}$ is the vector of mean values of Gaussians, which are GMM components; $\boldsymbol{\sigma} = (\sigma_1, \sigma_2, \ldots, \sigma_M)^{\mathrm{T}}$ is the vector of standard deviations of Gaussians, which are GMM components.

The vectors of GMM parameters $\boldsymbol{\theta} = \{\boldsymbol{\gamma}, \boldsymbol{\mu}, \boldsymbol{\sigma}\}$ can be estimated at the maximization step (M-step) of the EM algorithm:

$$\gamma_m = \frac{1}{N}\sum_{n=1}^{N}\alpha_{n,m};$$

$$\mu_m = \frac{\sum_{n=1}^{N}\alpha_{n,m}d_n}{\sum_{n=1}^{N}\alpha_{n,m}};$$

$$\sigma_m = \sqrt{\frac{\sum_{n=1}^{N}\alpha_{n,m}(d_n - \mu_m)^2}{\sum_{n=1}^{N}\alpha_{n,m}}}$$

The implementation of the EM algorithm is an iterative process, consisting of alternating repeats of expectation and maximization steps. This process starts from initial GMM parameters $\boldsymbol{\theta}^{(0)} = \left\{\boldsymbol{\gamma}^{(0)}, \boldsymbol{\mu}^{(0)}, \boldsymbol{\sigma}^{(0)}\right\}$ and ends with a convergence of the log-likelihood function $L(\boldsymbol{\theta}|\mathbf{d})$ while maximizing its value at the observed data $\mathbf{d}$:

$$L(\theta|\mathbf{d}) = \ln\prod_{n=1}^{N}p(d_n|\theta) = \sum_{n=1}^{N}\ln\sum_{m=1}^{M}\frac{\sigma_m}{\sqrt{2\pi\sigma_m^2}}\exp\left[-\frac{(d_n-\mu_m)^2}{2\sigma_m^2}\right];$$

$$L(\boldsymbol{\theta}|\mathbf{d}) \to \max,$$

where $p(d_n|\boldsymbol{\theta})$ is the value of the GMM probability density function $p(d)$, which is expressed in (1), for the n-th element of data $\mathbf{d}$ at the GMM parameters $\boldsymbol{\theta}$.

$$p(d) = \sum\nolimits_{m=1}^{M} \gamma_{\mathrm{m}} \mathcal{N}\left(\mathrm{d};\, \mu_{\mathrm{m}}, \sigma_{\mathrm{m}}^{2}\right) = \sum\nolimits_{\mathrm{m}=1}^{\mathrm{M}} \frac{\gamma_{\mathrm{m}}}{\sqrt{2\pi\sigma_{\mathrm{m}}^{2}}} \exp\left[- \frac{(\mathrm{d} - \mu_{\mathrm{m}})^{2}}{2\sigma_{\mathrm{m}}^{2}} \right], \quad (1)$$

where $\mathcal{N}\left(d;\, \mu_m, \sigma_m^2\right)$ is the m-th Gaussian of GMM.

A scheme for the EM algorithm, as for the iterative process, is shown in Fig. 2.

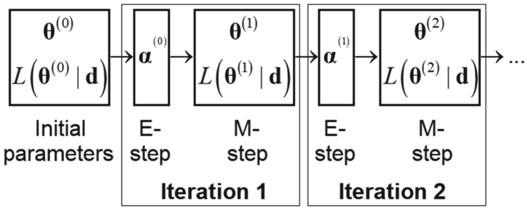

Fig. 2. Scheme for the EM algorithm, as for the iterative process.

In Fig. 2 and elsewhere in the paper the upper index in the notations $\boldsymbol{\theta}^{(\beta)} = \left\{\boldsymbol{\gamma}^{(\beta)}, \boldsymbol{\mu}^{(\beta)}, \boldsymbol{\sigma}^{(\beta)}\right\}$ and $\boldsymbol{\alpha}^{(\beta-1)}$ denotes the iteration number β within the EM algorithm.

There are two criteria for determining the convergence of the EM algorithm, i.e. stopping criteria for its iterative process, can be used:

- $L\left(\boldsymbol{\theta}^{(\beta)}|\mathbf{d}\right) - L\left(\boldsymbol{\theta}^{(\beta-1)}|\mathbf{d}\right) < \varepsilon$ where ε is a small positive value for the first criterion, which is sufficient to make a decision on convergence.
- $\left(\alpha_{n,m}^{(\beta-1)} \le \lambda\right) \vee \left(\alpha_{n,m}^{(\beta-1)} \ge 1 - \lambda\right)$, $n = \overline{1, N}$, $m = \overline{1, M}$, where λ is a small positive value for the second criterion, which is sufficient to make a decision on convergence.

When using either first or second criterion, $\boldsymbol{\alpha}^{(\beta-1)}$ is used to make a decision on clustering of homogenous data $\mathbf{d}$ into clusters.

The first criterion is better for estimation of GMM parameters $\boldsymbol{\theta}$, whereas the second one is better for clustering tasks. The second criterion is closely associated with the robustness of clustering because for $\lambda \to 0$ the values $\alpha_{n,m}^{(\beta-1)} \to 0$ or $\alpha_{n,m}^{(\beta-1)} \to 1$ are being obtained, which characterizes strong clustering behavior and a high degree of certainty of belonging of the n-th element d_n to the m-th cluster that is also the m-th Gaussian of GMM. However, it is not always possible to achieve such robust clustering, and it significantly depends on both the observed input data $\mathbf{d}$, initial GMM parameters $\boldsymbol{\theta}^{(0)}$, and the total number of clusters M, which can be taken for an internal parameter of the EM algorithm. In this regard, it is prudent to combine these two criteria in the stopping criteria for the EM algorithm in the following way:

$$\left\{L\left(\boldsymbol{\theta}^{(\beta)}|\mathbf{d}\right) - L\left(\boldsymbol{\theta}^{(\beta-1)}|\mathbf{d}\right) < \delta\right\} \vee \left\{\left(\alpha_{n,m}^{(\beta-1)} \le \lambda\right) \vee \left(\alpha_{n,m}^{(\beta-1)} \ge 1 - \lambda\right)\right\} \forall n, m, \quad (2)$$

where δ is a small positive value, and $\delta \ll \varepsilon$ for the first criterion within the combined criterion (2).

This approach may require an increase in the total amount of iterations, but improves the robustness of stopping criterion for the EM algorithm by the preferred second criterion within the combined criterion (2).

The clustering problem is complicated by the fact that the total number of clusters M can be unknown a priori. It also forms a background to features of application of the combined criterion (2).

There are known different modifications of the EM algorithm, in particular, the modification with adding of clusters [18] and the modification with removing of clusters [15, 30] during clustering. In the paper, we propose to use in a self-organization technique for sustainable infocommunications within CNS/ATM systems the modification of the EM algorithm with adding of clusters, starting with the initial total number of clusters $M = 2$. Such approach forms within the whole clustering framework an external iterative process, which is associated with increasing the value of M, with respect to an internal iterative process, which is associated directly with the EM algorithm and shown in Fig. 2.

Let M_ξ be the total number of clusters at the iteration ξ, starting with $\xi = 1$, within the external iterative process, i.e. the initial total number of clusters $M_1 = 2$ and $M_\xi = \xi + 1$, taking into account the above-mentioned modification of the EM algorithm with adding of clusters.

As a stopping criterion for the external iterative process, the criterion of minimum posterior estimated value of λ in the combined criterion (2) can be used. In this case, adding of clusters continues until the condition

$$\left\{\widetilde{\Lambda}_{\xi+1} \geq \widetilde{\lambda}_\xi\right\} \vee \left\{\widetilde{\lambda}_\xi \leq \lambda\right\} \tag{3}$$

is met, where $\widetilde{\lambda}_\xi$ is the posterior estimated value of λ at the ξ-th iteration of external iterative process. The value of $\widetilde{\lambda}_\xi$ has a meaning that

$$\left(\alpha_{n,m}^{(\beta-1)} \leq \widetilde{\lambda}_\xi\right) \vee \left(\alpha_{n,m}^{(\beta-1)} \geq 1 - \widetilde{\lambda}_\xi\right) \forall n, m$$

at the last iteration β within the ξ-th iteration of external iterative process.

Results of clustering at the total number of clusters M_ξ are being taken into account for the self-organization of sustainable infocommunication system within CNS/ATM systems.

The initial GMM parameters $\boldsymbol{\theta}^{(0)}$ can be determined using for initial approximation the principle of equidistance between clusters and the three-sigma rule of thumb [31] for a width of clusters $m = \overline{1, M}$, which are Gaussians of GMM:

$$\gamma_m^{(0)} = 1/M;$$

$$\mu_m^{(0)} = \min(d) + \frac{\max(d) - \min(d)}{M}\left(m - \frac{1}{2}\right); \tag{4}$$

$$\sigma_m^{(0)} = \frac{\max(d) - \min(d)}{6M}.$$

The location of Gaussians of GMM $\mathcal{N}\left(d; \mu_m, \sigma_m^2\right)$ (i.e., clusters) at the initial GMM parameters $\boldsymbol{\theta}^{(0)}$, which are determined by (4), are shown in Fig. 3.

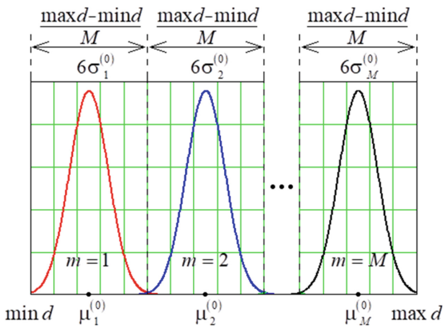

Fig. 3. Location of Gaussians (clusters) at the initial GMM parameters.

3.2 Norm Transformation Based Filtering

The norm (metric) transformation based filtering approach serves to limit possible influence of outliers and anomalies in the observed input data $\mathbf{d}$. This filtering is carried out through the transformation of $\mathbf{d}$ using a non-Euclidian norm:

$$\mathbf{d}^* = \mathcal{F}_2^{-1}[\mathcal{F}_{\mathrm{NE}}(\mathbf{d})], \tag{5}$$

where $\mathbf{d}^*$ is the filtered observed input data $\mathbf{d}$; $\mathcal{F}_{\mathrm{NE}}(\cdot)$ denotes the transformation in a non-Euclidian norm; $\mathcal{F}_2^{-1}(\cdot)$ denotes the inverse transformation in the Euclidian ℓ^2 norm.

A scheme for the norm transformation based filtering approach under consideration is shown in Fig. 4.

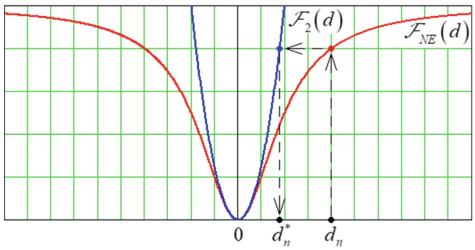

Fig. 4. Scheme for the norm transformation based filtering approach.

The transformation in a non-Euclidian norm $\mathcal{F}_{\mathrm{NE}}(d)$ can be based on different functions, which are bounded from above or, at least, characterized by their moderate values for large absolute values of argument d in comparison with a quadratic function in case of ℓ^2 norm (the example is shown in Fig. 4).

The most common kinds of non-Euclidian norms, which are used in statistical signal and data processing, at their core use functions such as [22, 32]:

- Magnitude function $\mathcal{F}_1(d) = |d|$, which is instrumental in describing Manhattan ℓ^1 norm.

- Hyperbolic function $\mathcal{F}_{21}(d) = \sqrt{s^2 + d^2} - s$.
- Geman-McClure function $\mathcal{F}_{20}(d) = d^2/(s^2 + d^2)$.

The functions $\mathcal{F}_{21}(d)$ and $\mathcal{F}_{20}(d)$ contain parameter s ($s \geq 0$), which determines their behavior. For example, for $|d| \ll s$ the behavior of $\mathcal{F}_{21}(d)$ and $\mathcal{F}_{20}(d)$ is close to the quadratic function $\mathcal{F}_2(d) = d^2$ that can be seen in Fig. 5, as well as $\mathcal{F}_{21}(0) = \mathcal{F}_{20}(0) = \mathcal{F}_2(0) = 0$.

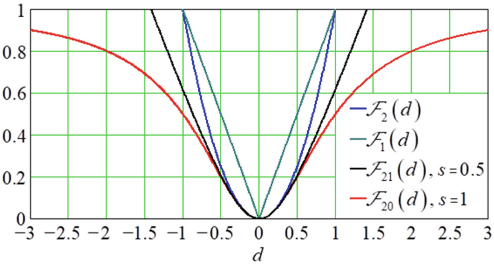

Fig. 5. Functions $\mathcal{F}_2(d)$, $\mathcal{F}_1(d)$, $\mathcal{F}_{21}(d)$, and $\mathcal{F}_{20}(d)$.

In the case of $s = 0$, $\mathcal{F}_{21}(d) = \mathcal{F}_1(d)$ (i.e. $\mathcal{F}_{21}(d)$ represents d in ℓ^1 norm), and $\mathcal{F}_{20}(d|d \neq 0) = 1$ (i.e. $\mathcal{F}_{20}(d)$ represents d in ℓ^0 "norm" as the number of non-zero elements d).

Among the considered examples, the Geman-McClure function [33] is of particular interest for the norm transformation based filtering because of its bounded from above behavior, i.e. $0 \leq \mathcal{F}_{20}(d) < 1$ for finite values of d.

The transformation (5) when using the Geman-McClure function and $d_n \geq 0$, $n = \overline{1, N}$, is expressed as:

$$\mathbf{d}^* = \mathcal{F}_2^{-1}[\mathcal{F}_{20}(\mathbf{d})] \iff d_n^* = d_n/\sqrt{s^2 + d_n^2}. \tag{6}$$

In the case of using the Geman-McClure function in norm transformation based filtering, an unsupervised automatic tuning of the parameter s is required as a part of self-organization ML technique. In the paper we propose to determine the parameter s using the following features of the Geman-McClure function:

- $\mathcal{F}_{20}\prime(d) = \frac{2ds^2}{(d^2+s^2)^2} > 0$ when $d > 0$, i.e. $\mathcal{F}_{20}(d)$ increases when $d > 0$.
- $\mathcal{F}_{20}''(d) = \frac{2s^2(s^2-3d^2)}{(d^2+s^2)^3}$ at $d = \sqrt{3}s/3$ or when $s = \sqrt{3}d$, $\mathcal{F}_{20}''(d) > 0$ on $d \in \left[0, \sqrt{3}s/3\right)$, and $\mathcal{F}_{20}''(d) < 0$ on $d \in \left(\sqrt{3}s/3, +\infty\right)$, i.e. the increasing of $\mathcal{F}_{20}(d)$ begins to decrease after the value of d where $s = \sqrt{3}d$.

In view of the above, it is advisable to tune the Geman-McClure function using the parameter s as the normalized arithmetic or geometric mean of the observed input data $\mathbf{d}$ (when $d_n \geq 0$, $n = \overline{1, N}$), s_A and s_G respectively:

$$s_A = \frac{\sqrt{3}\sum_{n=1}^{N} d_n}{N}; \tag{7}$$

$$s_{\mathrm{G}} = \sqrt{3}\left(\prod\nolimits_{n=1}^{N} d_n\right)^{\frac{1}{N}} = \exp\left(\frac{1}{2}\ln 3 + \frac{1}{N}\sum\nolimits_{n=1}^{N} \ln d_n\right) \tag{8}$$

The use of $s = s_{\mathrm{G}}$ is appropriate when $\min(d) \ll \max(d)$ in the observed input data **d**, e.g., for the case when the self-organization technique for sustainable infocommunications within CNS/ATM systems will use the wide band spectrum monitoring system from 30 MHz to 1800 MHz [34], i.e. $\min(d) = 3 \cdot 10^7$ Hz and $\max(d) = 1.8 \cdot 10^9$ Hz in possible DSA scenario.

Filtered data **d*** are used as the input data in the proposed ML self-organization technique.

4 Results and Discussions

4.1 Simulation of the Proposed Technique

Let a sustainable infocommunication system within CNS/ATM systems uses DSA scenario, and within the self-organization framework approach, an engineering goal boils down to an unsupervised automatic clustering of the available radio spectrum recourse into subsets of frequencies.

For this case, suppose that the observed input homogenous data **d** are the following $N = 21$ frequencies in MHz:

$$\begin{aligned}\mathbf{d} = &(2150, 2110, 728, 740, 3315, 3905, 3720,\\ &660, 2650, 2170, 2490, 17125, 2510, 710,\\ &6275, 6015, 6200, 5925, 5050, 780, 1910)^{\mathrm{T}}.\end{aligned} \tag{9}$$

As can be seen from (9), the element $d_{12} = 17125$ in the observed data **d** might be perceived as an outlier or anomaly if used definitions and criteria for them from [23].

Determine the parameter s using (7) and (8): $s_{\mathrm{A}} = 6362$; $s_{\mathrm{G}} = 4422$.

Taking into account that $\max(d)/\min(d) = 26$ and $\min(d) \ll \max(d)$ in the observed input data **d**, the parameter $s = s_{\mathrm{G}}$ in (6) is being used, and as a result the following data after norm transformation based filtering are obtained:

$$\begin{aligned}\mathbf{d}^* = &(0.437, 0.431, 0.162, 0.165, 0.600, 0.662, 0.644,\\ &0.148, 0.514, 0.441, 0.491, 0.968, 0.494, 0.159,\\ &0.817, 0.806, 0.814, 0.801, 0.752, 0.174, 0.396)^{\mathrm{T}}\end{aligned}$$

Let the criterion (2) is used as the stopping criterion for the internal ML iterative process with parameters $\delta = 0.1$ and $\lambda = 0.01$.

Adding of clusters continues until the stopping criterion (3) for the external ML iterative process is met. Simulation results for this case are obtained using developed by authors program and shown as a listing in Fig. 6.

β	$\gamma_1^{(\beta)}$	$\gamma_2^{(\beta)}$	$\gamma_3^{(\beta)}$	$\gamma_4^{(\beta)}$	$\gamma_5^{(\beta)}$	$\mu_1^{(\beta)}$	$\mu_2^{(\beta)}$	$\mu_3^{(\beta)}$	$\mu_4^{(\beta)}$	$\mu_5^{(\beta)}$	$\sigma_1^{(\beta)}$	$\sigma_2^{(\beta)}$	$\sigma_3^{(\beta)}$	$\sigma_4^{(\beta)}$	$\sigma_5^{(\beta)}$	$L(\theta^{(\beta)}\|d^*)$
Iteration $\xi = 1$ (external ML iterative process), total number of clusters (Gaussians of GMM) $M_1 = 2$																
0	0.500	0.500				0.353	0.763				0.068	0.068				−17.366
1	0.571	0.429				0.334	0.762				0.149	0.107				0.018
	Checking the criterion (2): $L(\theta^{(1)}\|d^*)-L(\theta^{(0)}\|d^*) = 17.384 > \delta$; e.g., $\alpha_{5,1}^{(0)} = 0.025$, $\lambda < \alpha_{5,1}^{(0)} < 1-\lambda \Rightarrow L(\theta^{(1)}\|d^*)$, $\alpha^{(0)}$ do not meet (2).															
2	0.591	0.409				0.348	0.764				0.161	0.114				0.268
	Checking the criterion (2): $L(\theta^{(2)}\|d^*)-L(\theta^{(1)}\|d^*) = 0.250 > \delta$; e.g., $\alpha_{5,1}^{(1)} = 0.384$, $\lambda < \alpha_{5,1}^{(1)} < 1-\lambda \Rightarrow L(\theta^{(2)}\|d^*)$, $\alpha^{(1)}$ do not meet (2).															
3	0.603	0.397				0.355	0.766				0.167	0.115				0.330
	Checking the criterion (2): $L(\theta^{(3)}\|d^*)-L(\theta^{(2)}\|d^*) = 0.062 < \delta$; e.g., $\alpha_{5,1}^{(2)} = 0.459$, $\lambda < \alpha_{5,1}^{(2)} < 1-\lambda \Rightarrow L(\theta^{(3)}\|d^*)$ meets (2).															
Checking the criterion (3): $\tilde{\lambda}_1 = 0.459$ ($\alpha_{5,1}^{(2)} = \tilde{\lambda}_1$), $\tilde{\lambda}_1 > \lambda \Rightarrow \tilde{\lambda}_1$ does not meet (3); the condition $\tilde{\lambda}_2 \geq \tilde{\lambda}_1$ in (3) will be checked at $\xi = 2$.																
Iteration $\xi = 2$ (external ML iterative process), total number of clusters (Gaussians of GMM) $M_2 = 3$																
0	0.333	0.333	0.333			0.284	0.558	0.831			0.046	0.046	0.046			−22.875
1	0.303	0.410	0.286			0.214	0.527	0.826			0.102	0.084	0.067			2.244
	Checking the criterion (2): $L(\theta^{(1)}\|d^*)-L(\theta^{(0)}\|d^*) = 25.119 > \delta$; e.g., $\alpha_{2,1}^{(0)} = 0.223$, $\lambda < \alpha_{2,1}^{(0)} < 1-\lambda \Rightarrow L(\theta^{(1)}\|d^*)$, $\alpha^{(0)}$ do not meet (2).															
2	0.267	0.441	0.292			0.190	0.516	0.822			0.082	0.089	0.073			3.632
	Checking the criterion (2): $L(\theta^{(2)}\|d^*)-L(\theta^{(1)}\|d^*) = 1.388 > \delta$; e.g., $\alpha_{21,2}^{(1)} = 0.711$, $\lambda < \alpha_{21,2}^{(1)} < 1-\lambda \Rightarrow L(\theta^{(2)}\|d^*)$, $\alpha^{(1)}$ do not meet (2).															
3	0.242	0.460	0.298			0.166	0.509	0.818			0.035	0.089	0.076			8.056
	Checking the criterion (2): $L(\theta^{(3)}\|d^*)-L(\theta^{(2)}\|d^*) = 4.424 > \delta$; e.g., $\alpha_{6,3}^{(2)} = 0.215$, $\lambda < \alpha_{6,3}^{(2)} < 1-\lambda \Rightarrow L(\theta^{(3)}\|d^*)$, $\alpha^{(2)}$ do not meet (2).															
4	0.238	0.458	0.304			0.161	0.506	0.815			0.009	0.088	0.079			12.824
	Checking the criterion (2): $L(\theta^{(4)}\|d^*)-L(\theta^{(3)}\|d^*) = 4.768 > \delta$; e.g., $\alpha_{6,2}^{(3)} = 0.716$, $\lambda < \alpha_{6,2}^{(3)} < 1-\lambda \Rightarrow L(\theta^{(4)}\|d^*)$, $\alpha^{(3)}$ do not meet (2).															
5	0.238	0.451	0.311			0.161	0.504	0.812			0.009	0.086	0.081			12.867
	Checking the criterion (2): $L(\theta^{(5)}\|d^*)-L(\theta^{(4)}\|d^*) = 0.043 < \delta$; e.g., $\alpha_{6,3}^{(4)} = 0.351$, $\lambda < \alpha_{6,3}^{(4)} < 1-\lambda \Rightarrow L(\theta^{(5)}\|d^*)$ meets (2).															
Checking the criterion (3): $\tilde{\lambda}_2 = 0.351$ ($\alpha_{6,3}^{(4)} = \tilde{\lambda}_2$), $\tilde{\lambda}_2 < \tilde{\lambda}_1$, $\tilde{\lambda}_2 > \lambda \Rightarrow \tilde{\lambda}_2$ does not meet (3); the condition $\tilde{\lambda}_3 \geq \tilde{\lambda}_2$ will be checked at $\xi = 3$.																
Iteration $\xi = 3$ (external ML iterative process), total number of clusters (Gaussians of GMM) $M_3 = 4$																
0	0.250	0.250	0.250	0.250		0.250	0.455	0.660	0.866		0.034	0.034	0.034	0.034		−14.211
1	0.238	0.333	0.184	0.244		0.161	0.458	0.662	0.839		0.009	0.039	0.054	0.064		14.560
	Checking the criterion (2): $L(\theta^{(1)}\|d^*)-L(\theta^{(0)}\|d^*) = 28.771 > \delta$; e.g., $\alpha_{19,4}^{(0)} = 0.131$, $\lambda < \alpha_{19,4}^{(0)} < 1-\lambda \Rightarrow L(\theta^{(1)}\|d^*)$, $\alpha^{(0)}$ do not meet (2).															
2	0.238	0.332	0.164	0.266		0.161	0.457	0.651	0.830		0.009	0.039	0.053	0.068		14.883
	Checking the criterion (2): $L(\theta^{(2)}\|d^*)-L(\theta^{(1)}\|d^*) = 0.323 > \delta$; e.g., $\alpha_{19,3}^{(1)} = 0.353$, $\lambda < \alpha_{19,3}^{(1)} < 1-\lambda \Rightarrow L(\theta^{(2)}\|d^*)$, $\alpha^{(1)}$ do not meet (2).															
3	0.238	0.331	0.151	0.279		0.161	0.457	0.642	0.826		0.009	0.039	0.045	0.070		15.196
	Checking the criterion (2): $L(\theta^{(3)}\|d^*)-L(\theta^{(2)}\|d^*) = 0.313 > \delta$; e.g., $\alpha_{19,3}^{(2)} = 0.191$, $\lambda < \alpha_{19,3}^{(2)} < 1-\lambda \Rightarrow L(\theta^{(3)}\|d^*)$, $\alpha^{(2)}$ do not meet (2).															
4	0.238	0.333	0.141	0.288		0.161	0.458	0.636	0.824		0.009	0.039	0.033	0.071		15.615
	Checking the criterion (2): $L(\theta^{(4)}\|d^*)-L(\theta^{(3)}\|d^*) = 0.419 > \delta$; e.g., $\alpha_{6,4}^{(3)} = 0.076$, $\lambda < \alpha_{6,4}^{(3)} < 1-\lambda \Rightarrow L(\theta^{(4)}\|d^*)$, $\alpha^{(3)}$ do not meet (2).															
5	0.238	0.333	0.136	0.292		0.161	0.458	0.635	0.823		0.009	0.039	0.027	0.071		15.764
	Checking the criterion (2): $L(\theta^{(5)}\|d^*)-L(\theta^{(4)}\|d^*) = 0.149 > \delta$; e.g., $\alpha_{6,3}^{(4)} = 0.914$, $\lambda < \alpha_{6,3}^{(4)} < 1-\lambda \Rightarrow L(\theta^{(5)}\|d^*)$, $\alpha^{(4)}$ do not meet (2).															
6	0.238	0.334	0.136	0.293		0.161	0.458	0.634	0.822		0.009	0.039	0.026	0.071		15.765
	Checking the criterion (2): $L(\theta^{(6)}\|d^*)-L(\theta^{(5)}\|d^*) = 0.001 < \delta$; e.g., $\alpha_{6,4}^{(5)} = 0.095$, $\lambda < \alpha_{6,4}^{(5)} < 1-\lambda \Rightarrow L(\theta^{(6)}\|d^*)$ meets (2).															
Checking the criterion (3): $\tilde{\lambda}_3 = 0.095$ ($\alpha_{6,4}^{(4)} = \tilde{\lambda}_3$), $\tilde{\lambda}_3 < \tilde{\lambda}_2$, $\tilde{\lambda}_2 > \lambda \Rightarrow \tilde{\lambda}_3$ does not meet (3); the condition $\tilde{\lambda}_4 \geq \tilde{\lambda}_3$ will be checked at $\xi = 4$.																
Iteration $\xi = 4$ (external ML iterative process), total number of clusters (Gaussians of GMM) $M_4 = 5$																
0	0.200	0.200	0.200	0.200	0.200	0.230	0.394	0.558	0.722	0.886	0.027	0.027	0.027	0.027	0.027	−30.419
1	0.238	0.193	0.203	0.186	0.180	0.161	0.427	0.534	0.726	0.853	0.009	0.019	0.053	0.066	0.069	13.851
	Checking the criterion (2): $L(\theta^{(1)}\|d^*)-L(\theta^{(0)}\|d^*) = 44.270 > \delta$; e.g., $\alpha_{16,4}^{(0)} = 0.415$, $\lambda < \alpha_{16,4}^{(0)} < 1-\lambda \Rightarrow L(\theta^{(1)}\|d^*)$, $\alpha^{(0)}$ do not meet (2).															
2	0.238	0.179	0.209	0.193	0.181	0.161	0.426	0.525	0.726	0.846	0.009	0.018	0.058	0.076	0.076	14.252
	Checking the criterion (2): $L(\theta^{(2)}\|d^*)-L(\theta^{(1)}\|d^*) = 0.401 > \delta$; e.g., $\alpha_{18,4}^{(1)} = 0.427$, $\lambda < \alpha_{18,4}^{(1)} < 1-\lambda \Rightarrow L(\theta^{(2)}\|d^*)$, $\alpha^{(1)}$ do not meet (2).															
3	0.238	0.169	0.213	0.198	0.182	0.161	0.426	0.519	0.726	0.841	0.009	0.018	0.060	0.081	0.080	14.373
	Checking the criterion (2): $L(\theta^{(3)}\|d^*)-L(\theta^{(2)}\|d^*) = 0.121 > \delta$; e.g., $\alpha_{18,4}^{(2)} = 0.436$, $\lambda < \alpha_{18,4}^{(2)} < 1-\lambda \Rightarrow L(\theta^{(3)}\|d^*)$, $\alpha^{(2)}$ do not meet (2).															
4	0.238	0.162	0.214	0.203	0.182	0.161	0.426	0.514	0.725	0.838	0.009	0.018	0.060	0.084	0.083	14.435
	Checking the criterion (2): $L(\theta^{(4)}\|d^*)-L(\theta^{(3)}\|d^*) = 0.062 < \delta$; e.g., $\alpha_{18,4}^{(3)} = 0.441$, $\lambda < \alpha_{18,4}^{(3)} < 1-\lambda \Rightarrow L(\theta^{(4)}\|d^*)$ meets (2).															
Checking the criterion (3): $\tilde{\lambda}_4 = 0.441$ ($\alpha_{18,4}^{(3)} = \tilde{\lambda}_4$), $\tilde{\lambda}_4 > \tilde{\lambda}_3$, $\tilde{\lambda}_4 > \lambda \Rightarrow \tilde{\lambda}_4$ meets (3). Results of clustering at $M_3 = 4$ are taking into account.																

Fig. 6. Simulation results (listing).

As shown in Fig. 6, at the iteration $\xi = 4$ the condition for the external ML iterative process $\tilde{\lambda}_4 > \tilde{\lambda}_3$, which is a part of the stopping criterion (3), is met. Results of clustering at the iteration $\xi = 3$ are taken into account. This means that the filtered data $\mathbf{d}^*$ and the related input data $\mathbf{d}$ are organized into $M_3 = 4$ clusters with the following probabilities

$\alpha_{n,m}$ that the n-th element of input data **d** belongs to the m-th cluster:

$$\boldsymbol{\alpha}^{(5)} = \begin{pmatrix} 0.000 & 1.000 & 0.000 & 0.000 \\ 0.000 & 1.000 & 0.000 & 0.000 \\ 1.000 & 0.000 & 0.000 & 0.000 \\ 1.000 & 0.000 & 0.000 & 0.000 \\ 0.000 & 0.006 & 0.981 & 0.013 \\ 0.000 & 0.000 & 0.905 & 0.095 \\ 0.000 & 0.000 & 0.965 & 0.035 \\ 1.000 & 0.000 & 0.000 & 0.000 \\ 0.000 & 1.000 & 0.000 & 0.000 \\ 0.000 & 1.000 & 0.000 & 0.000 \\ 0.000 & 1.000 & 0.000 & 0.000 \\ 0.000 & 0.000 & 0.000 & 1.000 \\ 0.000 & 1.000 & 0.000 & 0.000 \\ 1.000 & 0.000 & 0.000 & 0.000 \\ 0.000 & 0.000 & 0.000 & 1.000 \\ 0.000 & 0.000 & 0.000 & 1.000 \\ 0.000 & 0.000 & 0.000 & 1.000 \\ 0.000 & 0.000 & 0.000 & 1.000 \\ 0.000 & 0.000 & 0.000 & 1.000 \\ 1.000 & 0.000 & 0.000 & 0.000 \\ 0.000 & 1.000 & 0.000 & 0.000 \end{pmatrix} \quad (10)$$

Using the criterion of maximum probability among posterior probabilities, the observed input data **d** are distributed over 4 clusters $\mathbf{d}^{(1)}$, $\mathbf{d}^{(2)}$, $\mathbf{d}^{(3)}$, and $\mathbf{d}^{(4)}$ as follows:

$$\begin{aligned} \mathbf{d}^{(1)} &= \{d_3, d_4, d_8, d_{14}, d_{20}\} = (728, 740, 660, 710, 780)^{\mathrm{T}}; \\ \mathbf{d}^{(2)} &= \{d_1, d_2, d_9, d_{10}, d_{11}, d_{13}, d_{21}\} \\ &= (2150, 2110, 2650, 2170, 2490, 2510, 1910)^{\mathrm{T}}; \\ \mathbf{d}^{(3)} &= \{d_5, d_6, d_7\} = (3315, 3905, 3720)^{\mathrm{T}}; \\ \mathbf{d}^{(4)} &= \{d_{12}, d_{15}, d_{16}, d_{17}, d_{18}, d_{19}\} \\ &= (17125, 6275, 6015, 6200, 5925, 5050)^{\mathrm{T}}. \end{aligned}$$

4.2 Discussions

Thus, the proposed ML self-organization technique for sustainable infocommunications within CNS/ATM systems boils down to an unsupervised self-organization of system parameters into ranges, which simplifies a general tuning of such infocommunications in dynamically changing conditions. These ranges can be frequency bands in DSA scenario, SNR ranges in SNR scenario, ranges of time durations and any other groups of parameters, which can be for the engineering component (see Fig. 1).

The proposed technique is based on the modification of EM algorithm with adding of clusters within the GMM framework, which is combined with the norm transformation based filtering approach using, in particular, the Geman-McClure function for a core of the norm.

The following features characterize the proposed technique:

- Only observed input data are required for a preliminary tuning (initial GMM parameters) and further processing, which provides a self-adaptation organizational component.
- Fault tolerance is provided by the norm transformation based filtering, which is carried out through the transformation of observed input data using a non-Euclidian norm and limits possible influence of outliers and anomalies in these data, e.g., the influence of element d_{12} in the data (9).
- Clustering of system parameters into ranges is implemented using the criterion of maximum probability among posterior probabilities $\boldsymbol{\alpha}$ with a high certainty, e.g., only 3 of 21 elements in the data (9), namely d_5, d_6, d_7, are organized using (10) into ranges with accuracy $\Delta\alpha > 0.001$ in the sense of the criterion of ideal clustering ($\alpha_{n,m} \to 0$ or $\alpha_{n,m} \to 1$ for $\forall n, m$).
- The total number of ranges is determined automatically using the stopping criterion (3) for the external iterative process within the proposed ML technique.
- The robustness of clustering can be evaluated by the value of $\overset{\sim}{\lambda}$, which shows a maximum deviation from the ideal clustering ($\alpha_{n,m} \to 0$ or $\alpha_{n,m} \to 1$ for $\forall n, m$), e.g., results of clustering of the data (9) are characterized by the value $\overset{\sim}{\lambda} = \overset{\sim}{\lambda}_3 = 0.095$ (see (10) and Fig. 6); in this case the value $\overset{\sim}{\lambda} = 0$ corresponds to the best robustness of clustering (there is no any uncertainty of clustering), and the value $\overset{\sim}{\lambda} = \overset{\sim}{\lambda}_\xi = 1/M_\xi = 1/(\xi + 1)$ corresponds to the worst robustness of clustering (there is no any certainty of clustering), taking into account that $\sum_{n=1}^{M_\xi} \alpha_{n,m} = 1$ for $\forall n, m$.
- Preliminary determination of the number of ranges, their bounds and other thresholds are not required.
- Observed input data may not necessarily be sorted in ascending order, or anything else.
- The total number of iterations is relatively small in comparison with the total number of elements in analyzed data, e.g., 18 internal iterations within 4 external iterations (see Fig. 6) was required for clustering of 21 elements, which are the data (9).

5 Conclusions

Modern infocommunications, in particular for aeronautical purposes, take into account sustainable and environment-friendly aspects. These aspects of infocommunications are mainly concentrated in SDG 9 “Industry, innovation and infrastructure” and SDG 11 “Sustainable cities and communities” within the Sustainable development framework. Self-organization, self-adaptation, fault tolerance and self-healing properties, which are promising for sustainable infocommunications, can be effectively realized in such systems due to ML and AI based cognitive approaches.

The paper has introduced the self-organization ML technique for sustainable infocommunications within CNS/ATM systems. The proposed technique is based on a modification of the EM algorithm with adding of clusters within the GMM framework. The proposed technique allows for an unsupervised self-organization of system parameters into ranges (e.g., frequency bands, SNR ranges, ranges of time durations and any other groups of homogenous parameters), which simplifies a general tuning of infocommunications in dynamically changing conditions in aviation.

A feature of the proposed technique is the use of norm transformation filtering to restrict possible influence of outliers and anomalies in input system parameters. Such norm transformation filtering, which uses the Geman-McClure function based norm, is analyzed in detail. The main advantage of the proposed technique is the fact that only observed input system parameters are required for all stages of data processing. Setting of initial parameters, stopping criteria for internal and external iterative ML processes within the proposed technique are substantiated and analyzed.

The described evaluation of robustness for the proposed technique allows showing in terms of uncertainty for a distribution of probabilities how far an obtained clustering from ideal one. An example of simulation of the proposed technique for DSA scenario, which presents an unsupervised automatic clustering of the available radio spectrum recourse (21 frequencies including 1 possible anomalous value) into 4 frequency bands, is shown in the paper. The example also shows that the proposed technique has an acceptable computational cost (18 internal ML iterations within 4 external ML iterations are required for the clustering of 21 frequencies).

6 Future Scope

Prospects for applying the proposed ML self-organization technique for sustainable infocommunications within CNS/ATM systems are also in the field of statistical data processing for modern green communications [35–37], sustainable decision-making techniques [38], sustainable communications for healthcare [39], self-sustainable UAV-assisted wireless networks [40], sustainable communications in 5G/6G wireless sensor networks [41] and other technologies, which are connected with sustainable and environment-friendly applications.

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