The detection methods of dynamic objects

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Abstract. The article deals with the application of cluster analysis methods for solving the task of aircraft detection on the basis of distribution of navigation parameters selection into groups (clusters). The modified method of cluster analysis for search and detection of objects and then iterative combining in clusters with the subsequent count of their quantity for increase in accuracy of the aircraft detection have been suggested. The course of the method operation and the features of implementation have been considered. In the conclusion the noted efficiency of the offered method for exact cluster analysis for finding targets has been shown.

1. Introduction
The main task of the airspace using is the detection of the level of danger of the observed aircraft (A) and the distribution into the appropriate groups: «airplane, in a distress», «unidentified air object», etc. In the conditions of war the detection and the recognition of an air attack weapon is necessary for their ranging in a priority, the subsequent target distribution by means of warning radar. Detection A in the airspace is the task of radiolocation. The analysis of space and the determination of parameters of objects moving (navigation parameters) are carried out through radar stations (radar station) [1]. For detection of the aircraft and furthermore their identification (the determination of belonging to a certain class or type) information systems working in a radar wave range are created and enhanced. In the case of cluster analysis the tags of source objects initially have not been set, and even the input set can be unknown.

Aircraft is characterized by the following key navigation parameters:
- carrier frequency of \( f_c \) by which the frequency band of operation of an object is determined;
- power level of signal \( P \) by which it's possible to evaluate an object distance;
- aircraft heading \( v \), by which the direction of the airplane in space is evaluated;
- angle of the heel \( \gamma \) and the tangage angle \( \psi \), necessary for determination of the provision of A concerning its longitudinal and lateral axes.

The complexity of this task is provided by the complexity of the separation of aircraft in a specified frequency range. The difficulties occur then the extensive distribution of networks of the mobile communication 4G working in the same range of the frequency channel has been spread and it complicates the data handling. It compels to improve the algorithms of dynamic objects detection in the air space.

2. The problem statement
Let's assume the sequence of the navigation parameters to be presented in the form of input vector of characteristics of a \( p \)-object in the airspace \( x^p = (x_1^p, x_2^p, ..., x_i^p, ..., x_N^p) \), where \( p = \frac{1}{|X|} \) – index number of the aircraft from the input set of objects \( X \), \( x_i^p \) – \( i \)-th property of the \( p \)-th aircraft, \( i = \frac{1}{N} \),
$N$ – input set of the characteristics of the $p$-object. The set of the aircraft $X$, by means of the certain clustering method is dynamically distributed into groups (clusters). The created clusters $c_j$ comprise navigation parameters $p$-th aircraft $c_j = (x^1, ..., x^n) \in X$, where $j = 1, \ldots, M$, $M$ – quantity of clusters. Each input aircraft (further – object) shall be carried to one of the available clusters $c_j$. During the mathematical description of the degree of the similarity of objects, the Euclidean metrics is applied [3]. It represents the geometrical distance in a multivariate space.

$$d(x^p, c_j) = \sqrt{\sum (x^p_i - c_{mj}^j)^2}. \quad (1)$$

Its application is justified if the metric space matches geometrical space. The characterizing parameters of a cluster are: core $m(c_j)$, which are defined as follows:

$$m(c_j) = \sum_{i=1}^{n} u_{ij} x_i^p,$$

where $u_{im}$ – element of the partition matrix $U=(u_{ij})$, such that:

$$u_{ij} = \begin{cases} 1, & \text{for } d(x^p, c_j) \rightarrow \min; \\ 0, & \text{else}. \end{cases} \quad (2)$$

and the cluster radius $R$ is the distance between the core of the cluster and the object as far from the core $x^p$:

$$R = \max \{d(x^i - c_j) \}, x^i \in c_j.$$

The efficiency of the detecting aircraft, owing to a fuzzy clustering on the basis of the concepts described above is planning to increase.

3. Clustering methods of radarspace

In the most modern systems of the navigation parameters processing obtained from the locator, two types of clustering methods are used:

- “learning with a teacher” – differs in the fact that there is an additional information about input objects a priori. The implementation of this type of a clustering takes place in methods of an accurate clustering $k$-means;
- “learning without a teacher” – differs in the fact that the information concerning objects is unknown as well as their exact quantity is not known. Usually the tasks of data analysis of this kind use the methods of fuzzy clustering $c$-means;

Clustering by $k$-means [4] method breaks a set of objects of some (generally vectorial) space into quantity of clusters of $M$ unknown yet. $x^p$ – objects are divided into clusters again and again, according to the new center that is the closest to the selected metrics. The purpose of this method is to minimize the medium square root deviation quantity in the points of each cluster. The cycle has come to an end after the number of iterations set has passed (a priori). However the accurate clustering has the shortcoming connected to the combination of objects on the boundaries of clusters which is corrected in the indistinct methods.

The indistinct clustering by method $c$-means [5] makes partition of an input set of objects in clusters, using the function of accessory $\mu(x^p) \in [0,1]$, which defines the degree of an object belonging to a cluster. The difference of a level of accessory of accurate partition from indistinct is that function values $\mu(x^p)$ from an interval $[0,1]$, but not from a two-element set $(0,1)$ [6]. Taking into account this fact, the method $c$-means does not require the setting of the specific quantity of clusters with the introduction of a condition of the method stop.

In the case when the operator precisely defines the number of the purposes (dynamic objects in space), by means of the visual analysis the screen of the indicator will not demand the complicated methods of a clustering, such as $c$-means, and the sufficient efficiency will be shown by the $k$-means method. But in a situation when it is visually difficult to define the number of aircraft precisely and the standard methods of recognition become less effective, the use of a method $c$-means will be the best option.
However for the solution of an objective, it is required to introduce some modifications to the existing method, for increase in accuracy of A determination.

4. The modified method FCR_DV

Clustering methods on the basis of a mathematical apparatus of fuzzy logic are effective in search of relatively close metrics of objects [7]. It is explained by the fact that the method $c$-means creates the matrix of distribution of $U$ more precisely owing to the function of accessory $\mu(x^p)$. However, for increase in efficiency of cluster analysis, the required method is to be modified. The modification of a method $FCR_DV$ (Fuzzy Clustering with Recalculation and Deleting Void) is the following:

- recalculation of centers and radiuses of clusters for distribution of objects in it;
- introduction of criteria of the clusters adjacency and assessment procedure;
- checking of the combining of the similar clusters by special criteria;
- determination and deleting void clusters.

For the determination of an object accessory to a cluster the symmetric Gaussian function of accessory $\mu(x^p)$ is chosen:

$$\mu(x^p) = \exp\left[-\left(\frac{x^p - c_j}{2 \cdot \delta}\right)^2\right],$$

where $\delta$ is a tuning property of the accessory function equal to the estimated quantity of clusters in an initialization step. Vector accessory level $x^p$ to cluster is defined as follows:

$$\mu(x^p) = \max\left[\mu(x^p_1), \mu(x^p_2), ..., \mu(x^p_k), ..., \mu(x^p_N)\right].$$

To consider a level of accessory of objects to two next clusters $c_j$ and $c_k$, where $k \neq j, k \in M$ let's introduce the changes into a formula (1), taking into account a formula (3). Thereafter function of distance (metrics) will take the following form:

$$d(x^p, c_j) = \sqrt{\sum (\mu(x^p) - (x^p - c_j))^2}, x_j \notin c_j.$$ 

Values increase at a distance decrease between a vector of an object data and a cluster. Therefore the value of the function of accessory is more $\mu(c_j) > \mu(c_k), k \neq j$, where clusters are adjacent located in space $c_j$ and $c_k$, and as a criterion of two clusters association – cluster radius. The more objects are removed from clusters, the less value for making decisions on association will be.

Let's suppose that it is required to unite two objects with navigation parameters $x^1$ and $x^2$ in a cluster and at evaluation of the accessory functions (3), their degrees became equal, i.e. $\mu(x^1) = \mu(x^2) = 0.5$. At adjacent values it is possible to consider that a measure of proximity is the expression:

$$\tilde{d} = |\mu(x^p) - \mu(x^q)|.$$

Thereafter criterion of association of clusters is expression:

$$\alpha = |(\min(\mu(x^1), \min(\mu(x^2))) - 0.5| \geq \tilde{d}.~$$

However, after carrying out a clustering of the next entrance vector some clusters can’t have the vectors of data objects adjacent to them. Therefore, they have to be removed from the list, i.e. they are removed from a set of clusters (see Tab. 1). For the identification of empty clusters the variable $V(j)$ satisfying the equality is introduced:

$$\sum_{j=i}^{M} V(j) = L,$$

where $L$ – quantity of objects in initial set. Structurally the scheme of the FCR_DV method is present in fig. 1. Step by step the method looks as follows:
Step 1. To create the list of objects and the list of clusters, initializing the primary splitting according to the scheme: “ten objects in one cluster”. On the basis of the accepted splitting to create a matrix of splitting U according to (2).

Step 2. To calculate metrics between objects from a great number of X and the centers of clusters.

Step 3. To update the matrix of splitting U according to the current splitting. To recalculate the centers and radiuses of clusters of R.

Step 4. To check the proximity of clusters on the basis of criteria (4) and (5). In the case of a successful checking to execute association of objects from the close clusters and the subsequent removal of empty clusters.

Step 5. If after passing the previous iteration, the content of the list of clusters and the matrix of splitting U wouldn’t change, then go to Step 6, else go to Step 2.

Step 6. The end.

**Figure 1.** Work scheme of method FCR_DV.
Table 1. Estimated values of criterions of combined clusters

| Clusters  | Measure of a similar of clusters $\hat{d}$ | Criteria of combining $\alpha$ | Acceptance |
|-----------|--------------------------------------------|-----------------------------|------------|
| 1 and 2   | 0.9                                       | $|0.8 - 0.4| \leq 0.9$ or $|0.2 - 0.4| \leq 0.8$ | Don't combined |
| 2 and 3   | 0.3                                       | $|0.8 - 0.4| \geq 0.4$ or $|0.2 - 0.4| \leq 0.4$ | Combined   |
| 1 and 3   | 0.8                                       | $V(3) = 0$                  | Void       |

5. The results of experiments

To show the effectiveness of the proposed solution the comparative analysis of its work the clustering method c-means is carried out. As input data the navigation parameters are used: carrier frequency $f_c$, power level of signal $P$, aircraft heading $v$, angle of heel $\nu$, tangage angle $\psi$. Input datas are created by means of a specialized package of the software consisting of two program modules. By means of the first module it's simulated flight trajectories of 40 objects. The second module is intended for formation of a pack of impulses for the modelled trajectory. The realization of the offered $FCR_DV$ method is executed in the C# programming language. By virtue of means of program tools STATISTICA 10 (firm StatSoft), method c-means is realized.

As a result, the experimental cluster analysis has been conducted (see Tab. 2) by the means of the methods described above (seven experiments).

Table 2. Output of clustering methods.

| Navigational parameters | Clustering method | A Iterations | Count experiments | Relative error of method |
|-------------------------|-------------------|--------------|-------------------|--------------------------|
| Carrier frequency $f_c$, [MHz] | c-means | 35           | 11               | 5                | 2.2%                     |
|                         | $FCR_DV$         | 43           | 21               | 6                | 1.3%                     |
|                         |                   | 45           | 23               | 1                |                          |
| Power level $P$, [dBm]  | c-means          | 38           | 12               | 6                | 2.7%                     |
|                         | $FCR_DV$         | 40           | 21               | 5                | 0.9%                     |
|                         |                   | 39           | 23               | 2                |                          |
| Heading $v$, [deg.]    | c-means          | 42           | 12               | 5                | 4.7%                     |
|                         | $FCR_DV$         | 40           | 27               | 5                | 0.9%                     |
|                         |                   | 39           | 27               | 2                |                          |
| Heel $\nu$, [deg.]    | c-means          | 39           | 12               | 7                | 0.01%                    |
|                         | $FCR_DV$         | 40           | 20               | 7                | 0%                       |
| Tangage $\psi$, [deg.]| c-means          | 39           | 12               | 7                | 0.01%                    |
|                         | $FCR_DV$         | 40           | 20               | 7                | 0%                       |

The relative accuracy has been calculated by the means of the $t$-test method [9]. Seven experiments as a result of which statistical data on the recognizable aircraft are obtained have been conducted. The analysis of table 2 has shown that the error of the $FCR_DV$ method is less than of c-means method.
According to the analysis of a carrier frequency it is visible that both methods do not recognize the precise number of aircraft. The method c-means recognizes in 5 cases 33 air objects, in 2 cases 35 air objects that less than the true quantity of objects \( |X| = 40 \).

At the same time, the \( FCR_DV \) method recognized 43A for six experiments and 45 A for one experiment that exceeds the true quantity. However considering a difference between the number of undetected A and excess A, there is an improvement in results of the \( FCR_DV \) method since from the point of view of radiolocation it is better to detect three targets than not to find five definite targets.

The cluster analysis of the value of power level of \( P \) has shown better results, than the previous one (see fig. 2). Owing to the cluster analysis by c-means from 38 to 42 air objects are revealed, and 38 A is found in overwhelming number of experiments. The \( FCR_DV \) method detects up to 39-40 objects that shows its effectiveness of rather true number of objects.

![Figure 2](image1.png)

**Figure 2.** Comparison recognition accuracy of A (line 1 – method c-means; line 2 – method \( FCR_DV \)): a) – carrier frequency; b) – power level.

The possible larger count of iterations of the \( FCR_DV \) method creates the increase in accuracy of discernment. But at the same time, in the presence of other data set, the offered \( FCR_DV \) method looses in speed of c-means method.

The method \( FCR_DV \) proceeds the deleting and recalculation centers and radiiuses of clusters allow to have more precisely objects concerning their «coordinates» in a metric space. In fig. 4 the comparison of two methods which indicates the exceeded quantity of the recognizable objects c-means is connected with the method with the existence of void clusters which were removed in the \( FCR_DV \) method has been presented.

![Figure 3](image2.png)

**Figure 3.** Comparison recognition accuracy of A (line 1 – method c-means; line 2 – method \( FCR_DV \)): a) – heading; b) – heel.
The analysis of the aircraft heading, angles heel or tangage (the cluster analysis on angles heel or tangage identical), are united by one common case connecting two schedules (see fig. 3). The accuracy of an objects detection differs in two undetected A. The cluster analysis of two angles of heel and tangage has shown identical results. Basing on it, it can be said that both methods results on quantity of the found objects are similar, but the distinction in the count of iterations is observed.

6. Conclusion

In the work the results have presented the solution of the problem of dynamic objects detected by means of the modified method FCR_DV. This decision gives an opportunity to define the quantity of clusters in the course of work and to proceed the repeated reorganization of clusters, to define and delete empty clusters for an increase in the accuracy of the distribution.

By means of the modified FCR_DV method it was succeeded to mark out the larger quantity of aircraft, than by means of an algorithm c-means. However the count of iterations of FCR_DV is higher, than at c-means method. This fact says that if we have a larger volume of data the cluster analysis will require more time. In the future it is planned to modify clustering methods like “learning without teacher” for applying them at stages of assessment of probabilities of a distribution of objects and making decisions for combining them.

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