Algorithm of work multisensory system is shown in Fig. 3.

If necessary set of sensors can be changed. You can add more sensors to the system, but it requires editing code. Since sensors have cross-sensitivity, we can uniquely identify the gas that was detected.

Conclusions

This paper describes the designing multisensory system for monitoring gases based on STM32F407 microcontroller and using cross-sensitivity sensors, that can not only detect the available gas in the environment, but also uniquely identify it. In this paper the algorithm of the system, which allows you to change the set of sensors is presented.

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FUZZY MODEL FOR RECOMMENDER SYSTEMS

НЕЧІТКА МОДЕЛЬ ДЛЯ РЕКОМЕНДАЦІЙНОЇ СИСИЕМИ

The paper analyzes the current state of development and application of recommendation systems, models and methods of construction of recommendation systems. It is shown that the most widely used method came into collaborative filtering. The method of fuzzy clustering is developed, which improves the accuracy of predicting ratings of products.

Key words: Recommender system, data mining, collaborative filtering, fuzzy clustering.

Проаналізовано поточний стан розробки та застосування рекомендаційних систем, моделей і методів побудови рекомендаційних систем. Показано, що найбільш широко використовується метод колаборативної фільтрації фільтрації. Розроблено метод нечіткої кластеризації, який підвищує точність прогнозування рейтингів продуктів.

Ключові слова: Рекомендаційні системи, інтелектуальний аналіз даних, колаборативна фільтрація, нечітка кластеризація.

Introduction

Recommendation system – a system working with a certain type of information, a filter system that recommend information items that can cause a user's interests. The typical recommendation system makes recommendations to users as input, aggregates and sends them to the appropriate recipients in the form of recommendations. Recommendation system compares the data collected from users and create a list of items recommended to the user. They are an alternative search algorithm because it helps users to find items and information that they would not find themselves.

Since the first works in the mid-1990s, recommendation systems have become the subject of intense scientific attention. During the last decade a lot of work has been done both theoretical and applied, dedicated to the development of recommendation systems. At present the problem of recommendation systems keeps to himself a lot of interest. In this area there remain many unsolved problems. Addressing these challenges promises many opportunities for practical application. This will allow users to cope with the huge amount of information, and provide them the tools making personalized recommendations. An example of a specific application of recommendation systems can serve a system recommendations of books, CD and other items at Amazon.com, movies on MovieLens, news on VERSIFI Technologies (former AdaptiveInfo.com).

In modern recommendation systems are widely used methods and models collaborative filtering. Model of collaborative filtering is user-item matrix **A** dimension mxn. Rows of the matrix correspond to the vector of users **U**, column correspond to the vector of items **I**. Each element of the matrix a_{ij} contains I_j product rating assigned by user U_i. The rating scale is estimated to be integers $a_{ij} \in \{1,2,3,4,5\}$.

The main problems in collaborative filtering method: a very large dimension and greate sparsity matrix **A**.

To solve these problems using an approach based on models. Originally formed descriptive model of user preferences, items and the relationship between them. Then recommendations are formed on the basis of the obtained model. The advantage of this approach is the availability of the model. It gives more insight generated recommendations and relationships in data availability. The formation of recommendations is divided into two stages: intensive training model in off-line mode and a fairly simple calculation based on the recommendations of the existing models in real time.

Fuzzy method for recommender systems

Perspective is the application of methods and models of clustering. Clustering allows divide the whole set of users and products to compact clusters. Each cluster contains the most similar objects. General clustering model can be represented as follows: **K** – set of items and users; $\mathbf{K_1}$, $\mathbf{K_2}$, ... $\mathbf{K_c}$ – clusters.

For a hard clustering the following conditions are performed:

$$\mathbf{K}_1 \cup \mathbf{K_2} \cup \mathbf{K} \cup \mathbf{K_c} = \mathbf{K} \tag{1}$$

$$\mathbf{K}_i \cap \mathbf{K}_j = \varnothing; \ \mathbf{K}_\mathrm{i}, \mathbf{K}_\mathrm{j} \neq \varnothing \tag{2}$$

$$|\mathbf{K}_1| + |\mathbf{K}_2| + \mathbf{K} + |\mathbf{K}_c| = |\mathbf{K}| \tag{3}$$

With a hard clustering each object belongs to one cluster.

For a fuzzy clustering the following conditions are performed:

$$\mathbf{K}_1 \cup \mathbf{K_2} \cup \mathbf{K} \cup \mathbf{K_c} = \mathbf{K} \tag{4}$$

$$\mathbf{K}_i \cap \mathbf{K}_j \neq \varnothing; \ \mathbf{K}_\mathrm{i}, \mathbf{K}_\mathrm{j} \neq \varnothing \, \forall i, j \quad i \neq j \tag{5}$$

$$|\mathbf{K}_1| + |\mathbf{K}_2| + \mathbf{K} + |\mathbf{K}_c| = c|\mathbf{K}| \tag{6}$$

where c is the number of clusters.

Let **Y** – matrix partition of objects into clusters. For a hard clustering the following conditions are performed:

$$y_i(l) = y_{il} = \begin{cases} 1; l \in \mathbf{C}_i \\ 0; l \notin \mathbf{C}_i \end{cases} \tag{7}$$

$$\sum_{l=1}^{n} y_{il} > 0; \forall i \tag{8}$$

$$\sum_{i=1}^{c} y_{il} = 1; \forall l \tag{9}$$

For a fuzzy clustering the following conditions are performed:

$$y_{il} \in \left]0,1\right[\tag{10}$$

$$0 < \sum_{l=1}^{n} y_{il} < n \qquad (11)$$

$$\sum_{i=1}^{c} y_{il} = 1 \qquad (12)$$

The classical model of collaborative filtering is to predict the unknown product rating for the active user by user-user or product-product model.

For a method user-user

$$p_{a,i} = \bar{r}_a + \frac{\sum_{u \in \mathbf{U}} (r_{u,i} - \bar{r}_u) w_{a,u}}{\sum_{u \in \mathbf{U}} |w_{a,u}|} \qquad (13)$$

where $p_{a,i}$ – rating ***i***-th item for active users; $\bar{r}_a$ – the average of the rating of the active user; $\bar{r}_u$ – average rating value of the ***u***-th user; $r_{u,i}$ – rating of the ***i*** item for ***u*** user; $w_{a,u}$ **–** coefficient of similarity for a rating vector of active user and rating vector of ***u*** user.

For the method of the item-item

$$p_{u,i} = \frac{\sum_{u \in \mathbf{U}} r_{u,n} w_{i,n}}{\sum_{u \in \mathbf{U}} |w_{i,n}|} \qquad (14)$$

where $w_{i,n}$ – coefficient of similarity for a rating vector of ***i*** item and ***n*** item.

In fuzzy clustering, each product belongs to each cluster. Degree of membership of each product to fuzzy cluster is determined by the characteristic function

$$y_{il} \in \left]0,1\right[, \; 0 < y_{il} < 1 \qquad (15)$$

$$\sum_{i=1}^{c} y_{il} = 1 \qquad (16)$$

Let $\mathbf{T}_l$ – vector of values characteristic function for *l* item. $\mathbf{M}_l = \mathbf{T}_l \times N$ – vector quantity of items with the highest ratings will be used in the forecast calculation formulas. M_{lc} – number of items from top-rated belonging to cluster ***c***.

Then the model method the user-user (17) and the item-item (18)

$$p_{a,i} = \bar{r}_a + \frac{\sum_{m=1}^{c} \sum_{s=1}^{M_{as}} w_{a,s} (r_{s,i} - \bar{r}_s)}{\sum_{m=1}^{c} \sum_{s=1}^{M_{as}} |w_{a,s}|} \qquad (17)$$

$$p_{u,i} = \frac{\sum_{m=1}^{c} \sum_{s=1}^{M_{as}} w_{u,s} r_{u,i}}{\sum_{m=1}^{c} \sum_{s=1}^{M_{as}} |w_{u,s}|} \qquad (18)$$

For clustering applied fuzzy c-means method, which minimizes the following functional

$$J_m(\mathbf{Y}, v) = \sum_{k=1}^{N} \sum_{i=1}^{c} (y_{ik})^m \|\mathbf{u}_k - \mathbf{v}_i\|_A^2 \qquad (19)$$

where $\mathbf{U} = \{\mathbf{u_1}, \mathbf{u_2}, \mathbf{K}, \mathbf{u}_N\}$-set of information objects; c – number of clusters; m – fuzziness factor; $\mathbf{Y}$ – fuzzy c-partition matrix; $\mathbf{v} = \{\mathbf{v_1}, \mathbf{v_2}, \mathbf{K}, \mathbf{v_c}\}$-set of vectors of the centers of fuzzy clusters; $\mathbf{v_i} = (v_{i1}, v_{i2}, \mathbf{K}, v_{in})$ – vector coordinates *i* – th of cluster centers.

C-means algorithm consists of the following steps.

1. Choose a random number of initial cluster centers and placement

$$2 < c < N \tag{20}$$

2. Choose option stops d .

3. Choose a fuzziness factor $m \in (1,\infty)$.

4. Calculate the initial values of the matrix elements of fuzzy partition $\mathbf{Y}^{(0)}$.

5. Calculate the cluster centers

$$\mathbf{v}_{\mathbf{i}}^{(l-1)} = \frac{\sum_{k=1}^{N} (y_{ik}^{(l-1)})^m \mathbf{u}_k}{\sum_{k=1}^{N} (y_{ik}^{(l-1)})^m}, \ 1 \le i \le c \tag{21}$$

6. Calculate the metric distance

$$d_{ik}^{(l-1)} = (\mathbf{u}_k - \mathbf{v}_i^{(l-1)})^T (\mathbf{u}_k - \mathbf{v}_i^{(l-1)}) \tag{22}$$

7. Calculate the matrix elements of fuzzy partition

$$y_{ik}^{(l-1)} = \frac{1}{\sum_{j=1}^{c} (\frac{d_{ik}^{(l-1)}}{d_{jk}^{(l-1)}})^{\frac{2}{(m-1)}}} \tag{23}$$

8. Check the stop condition

$$\left\| \mathbf{Y}^{(l)} - \mathbf{Y}^{(l-1)} \right\| < d \tag{24}$$

If the condition is met, then stop. Otherwise $\mathbf{Y}^{(l)} = \mathbf{Y}^{(l-1)}$, go to the step5.

Application of fuzzy clustering can improve the accuracy of forecasting rankings by taking into account degree of membership of each product to each cluster.

Conclusion

The paper analyzes the current state of development and application of recommendation systems, models and methods of construction of recommendation systems. It is shown that the most widely used method came into collaborative filtering. The method of fuzzy clustering is developed, which improves the accuracy of predicting ratings of products.

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SIMULATION OF MECHANICAL COMPONENTS INTEGRATED ACCELEROMETERS
МОДЕЛЮВАННЯ МЕХАНІЧНИХ КОМПОНЕНТІВ ІНТЕГРАЛЬНИХ АКСЕЛЕРОМЕТРІВ

In the paper the model of integrated accelerometer is presented. Obtained in an analytical form solution of the differential equation describing this model.

Key words: integral accelerometer, mathematical model, differential equation, boundary conditions.

Подано моделі інтегрованого акселерометра. Отримано в аналітичному вигляді рішення диференціального рівняння, що описує цю модель.

Ключові слова: інтегральний акселерометр, математична модель, диференціальне рівняння, граничні умови.

Introduction

Accelerometer – this device, which measure acceleration or overloads that occur during testing of vehicles and their systems. Single– and multi-axle models can determine the magnitude and direction of the acceleration as a vector quantity and can therefore be used to determine the orientation, vibration and shock. They are used in many portable electronic devices.

The accelerometer measures the projection of the full acceleration. Full acceleration is the resultant of the forces of nature nehravitatsiynoyi acting on the mass, referred to the value of the mass. The accelerometer can be used both to measure the projection of the absolute linear acceleration and mediocre projection of the gravitational acceleration. The latter property is used to create inclinometers. Accelerometer is a member of inertial navigation systems that are obtained by measuring their integrated to give the inertial velocity and coordinates media.

Model of integral accelerometer

According to the analysis of existing models of accelerometers, most of the models include ordinary differential equations of second order [1]. These models are based on consolidated mikroakselerometra to design circuits with lumped parameter spring-mass-damper [2], an example of which is given on (Fig. 1). Accordingly, for such a system of differential equations for the displacement axis is a function of the external acceleration:

$$m_x \frac{d^2x}{dt^2} + B_x \frac{dx}{dt} + k_x x = F_{zovn}, \qquad (1)$$
$$F_{zovn} = ma_{zovn}$$

k_x – spring stiffness; B_x – damping coefficient; m_x – mass; a_{zovn} – applied acceleration to the inertial mass of the accelerometer; x – displacement; F_{zovn}, – external force that is applied to the inertial mass of the accelerometer;