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A Smart Program Recommender System Based on the Hybrid Broadcast Broadband Television

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Abstract: In this paper, an improved version of smart program recommendation system based on Hybrid Broadcast Broadband Television (HbbTV) technology is proposed. The learning part which was based on the artificial neural network (ANN) has been enhanced by incorporating the genetic algorithm. Instead of assigning all users to the same ANN, clustering is introduced by utilizing preferred genre information obtained explicitly. The number of clusters is found automatically. Gathering the user data and presenting the television program recommendations to the user are realized by the HbbTV technology. The proposed system has been tested by the data from 248 people and has given successful results.

Karma Yayın Genişbant Televizyon Tabanlı Akıllı Bir Program Önerici Sistemi

Anahtar Kelimeler
Yapay Sinir Ağları, Kümeleme Algoritmaları, Sayısal TV, Genetik Algoritmalar, Öneri Sistemleri

Özet: Bu makalede, Karma Yayın Genişbant Televizyon (KygTV) teknolojisine dayanan akıllı program öneri sisteminin geliştirilmiş bir versiyonu sunulmuştur. Yapay sinir ağına (YSA) dayalı öğrenme kısmı, genetik algoritma eklenerek iyileştirilmiştir. Bütün kullanıcıları aynı YSA'ya atamaktansa, açık yollarla elde edilen tercih edilen tür bilgisi kullanılarak kümeleme yöntemi kullanılmıştır. Küme sayısı otomatik olarak bulunmuştur. Kullanıcı verisinin toplanması ve televizyon program önerilerinin kullanıcıya sunulması KygTV teknolojisi ile gerçeklenmiştir. Önerilen sistem 248 kişinin verisi ile test edilmiş ve sistemin başarılı sonuçlar verdiği görülmüştür.

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1. Introduction

Hybrid Broadcast Broadband Television (HbbTV) is a new standard published by the European Telecommunications Standards Institute for harmonizing the broadcast and broadband delivery of entertainment services to consumers through digital receivers [1]. It aims to improve the user television watching experience for consumers by enabling innovative, interactive services over broadcast and broadband networks.

An HbbTV application is a collection of HTML, JavaScript, CSS, XML and multimedia files constituting an interactive service. An HbbTV capable receiver can connect to both DVB via broadcast network and internet via broadband network. From the broadcast part (terrestrial, cable or satellite), it receives traditional audio/video content. HbbTV application signaling also comes from broadcast. From the broadband part, the device receives application data and on demand audio/video streaming. Broadband connection is also used for sending data from the receiver to the application server [2].

In the previous work of Topalli and Kilinc [1], utilization of HbbTV concept for smart program recommendation was explored. The idea of collecting user's program watching history by an HbbTV application running on a digital receiver, using these data to train an artificial neural network (ANN) on the broadcaster's server side, and sending programs matching to the ANN's output as recommendations via the same HbbTV application was not done before to the best of authors' knowledge and gave successful results.

The number of users whose watching histories were recorded was eight and due to the small number of participants a single ANN was used. However, clustering the users was proposed as a future work in order to cope with the increasing number of users and keep the number of users handled by each neural network under control.

The method proposed here focuses on the improvements of this previous work [1], when a large number of users are present, a case more close to the real world. For this purpose, a data set is collected from 248 people. Before the ANN learning phase, the optimum number of clusters is first found and the data set is clustered into the smaller groups by the Genetic Algorithm (GA). Then a separate ANN for each cluster is formed and trained by parallel processing.

HbbTV is again proposed as the communication path between the receiver and the server to send the user's data and to receive and present the recommendations. In addition to the age and gender information, this time users are asked to specify their program genre preferences for three different time of the week during the registration screen of the HbbTV application. These data are then used to cluster the users and assign them to the correct ANN.

The work of Topalli and Kilinc [1] also gives a summary of recent works about the television program recommendation systems for both Internet connected and unconnected devices which are DVB (digital video broadcasting) or IPTV based [3]-[14]. But none of the works aforementioned there has used a worldwide specification like HbbTV for data gathering or content recommendation.

Soares and Viana [15] propose a Web based application which allows users to navigate and access broadcast and on-demand television content by presenting recommendations based on collaborative and content based filtering. Their algorithm calculates the similarity between items and between users to predict the rating that users would assign to television programs. They use MPEG-7 based TV-Anytime standard to get description, selection, acquisition and manipulation of content for both broadcast and online services. The user profile required by their recommendation engine is constructed using information collected both explicitly (rating given to watched programs) and implicitly (the time of day, etc.). Since this method does not run on a digital receiver, they use FlowPlayer, an Open Source Video Player developed in Flash.

On clustering, Krovi is one of the first to investigate the potential feasibility of GA usage in his research [16]. Krishna and Murty [17] propose a novel hybrid GA to find a globally optimal partition of a given set of data into a specified number of clusters. They use a classical gradient descent algorithm, K-means algorithm, instead of crossover. The GA-clustering proposed by Maulik and Bandyopadhyay [18] uses searching capability of GAs for the purpose of appropriately determining a fixed number K of cluster centers. The clustering metric that has been adopted is the sum of the Euclidean distances of the points from their respective cluster centers. Lin, Yang and Kao [19] have proposed a GA-based unsupervised clustering technique that selects cluster centers directly from the data set, allowing it to speed up the fitness evaluation by constructing a look-up table in advance, saving the distances between all pairs of data points, and by using binary representation rather than string representation to encode a variable number of cluster centers. Bandyopadhyay and Maulik [20]have exploited the searching capability of GAs for automatically evolving the number of clusters as well as proper clustering of any data set. A new string representation, comprising both real numbers and the do not care symbol, are used in order to encode a variable number of clusters. Kudova proposed Clustering Genetic Algorithm [21] which is capable of optimizing the number of clusters for tasks with well-formed and separated clusters.

Since HbbTV is a widely accepted public consumer electronics standard for digital receivers and most of the recent devices support it, like the original work [1] the model proposed here is also device-agnostic and can reach many people using different consumer devices.

This paper consists of the following parts: Section II gives details on the proposed method; obtained results are given in Section III; discussion and conclusion can be found in Section IV.

2. Material and Method

The proposed algorithm consists of the following phases: explicit and implicit data gathering by the HbbTV application, clustering by the GA, learning by the ANNs, and recommending programs again by the HbbTV.

The data gathering part is done by the HbbTV application running on the receiver. The HbbTV application sends data implicitly and explicitly from multiple users to the server. Then the users are clustered by the GA at the server side using the explicitly collected data. A separate ANN is formed for the users of each cluster. These ANNs are trained and tested at server by both explicit and implicit data. Once recommendations are ready, the same HbbTV application fetches the

recommendations from the server and shows them on the TV screen.
Clustering and learning are repeated at the server side periodically, for example every night so that the new users of that day can be included in the system. Flowchart of this periodic algorithm can be drawn as in Figure 1.

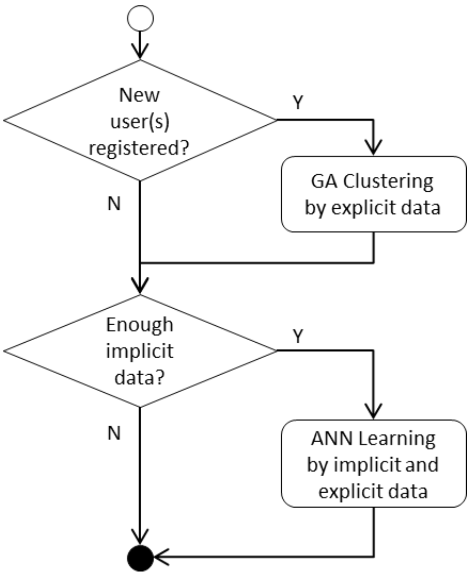

Figure 1. Flowchart of the periodic (daily) server operation

The method proposed here is an improved version of the original work of Topalli and Kilinc [1]. Tasks are again shared between the receiver and the server, lighter tasks such as data collection and recommendation presentation are carried on the receiver whereas heavy tasks such as GA clustering and ANN learning are performed on the server side. Different than the previous work, GA clustering and ANN learning per cluster have been introduced (Figure 2).

2.1. Explicit and implicit data gathering

Both explicit and implicit data are collected by an HbbTV application. Explicit data refer to the information entered by the user directly where implicit data are sent to the server without direct interaction of the user.

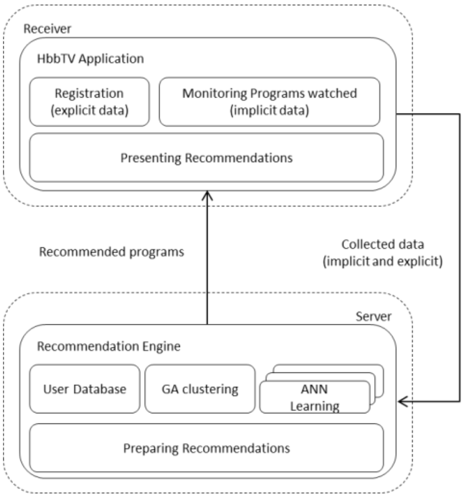

Figure 2. Block diagram of the proposed system

The written HbbTV application checks with the server whether the user has already been registered or not. If not registered, it pops up a window on the television screen and asks for user's consent, age, gender, and as an addition to the original work [1], the top five genre preferences for three different times of the week: weekday evenings, weekend day time, and weekend evenings. This explicitly gathered information is sent to the server and stored. This operation is done only once per receiver.

As before [1] the list of the genres is taken from the European Standard "Digital Video Broadcasting (DVB); Specification for Service Information (SI) in DVB systems" [22] with additional non-standard genres, "Turkish Movie (TM)", "Turkish Drama (TD)", "Foreign Movie (FM)", and "Foreign Drama (FD)", thinking that separate genres would give better results and beneficial to the Turkish consumers since local movies and dramas are very popular in Turkey.

After the registration, the HbbTV application continues to collect data while the user watches TV or on demand programs. In the first case, by getting the duration of the current program that the user is watching, the HbbTV application checks whether the user stays on the same channel during the 75% of the current program, accepts it as valid data and sends the details to the server to be added to the database. This is called implicit data gathering since it is done automatically by the system without any user input.

It is also possible for broadcasters to offer on demand programs via the HbbTV application. If the user selects a program from the on demand list and watches the program until the end, then that program is accepted as valid implicit data and the HbbTV application sends its genre to the server to be added to the database.

2.2. Clustering by the GA

HbbTV application collects data from many receivers belonging to people of different ages, genders, and genre preferences. The ones with similar features are assigned to the same clusters so that the learning phase can produce better results. GA is chosen as the clustering method by utilizing the data collected explicitly.

Cluster analysis is a technique, which is used to discover patterns and associations within data. More specifically, it is a multivariate statistical procedure that starts with a data set containing information on some variables and attempts to reorganize these data cases into relatively homogeneous groups [23].

In GAs, the parameters of the search space are encoded in the form of strings, called chromosomes. A collection of such strings is called a population. Initially, a random population is created, which represents different points in the search space. A fitness function is associated with each string that represents the degree of goodness of the string. Based on the principle of survival of the fittest, a few of the strings are selected and each is assigned a number of copies that go into the mating pool. Biologically inspired operators like cross-over and mutation are applied on these strings to yield a new generation of strings. The process of selection, crossover and mutation continues for a fixed number of generations or till a termination condition is satisfied [18]. The flow chart of this algorithm is shown in Figure 3.

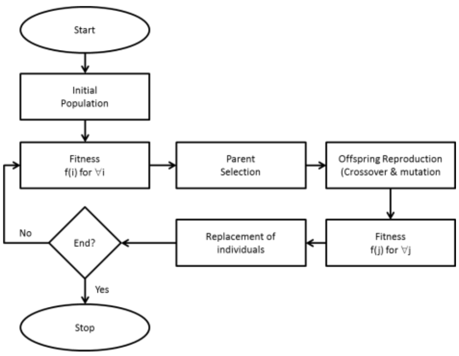

Figure 3. GA flow chart

In this work, genes of the chromosomes are age, gender, the first five preferences of weekday evenings (WDE), the first five preferences of weekend day time (WED), and the first five preferences of weekend evenings (WEE). Age is represented by a single value, the minimum of the corresponding age group. Gender is given as either 0 or 1. Genre preferences are represented by a number between 1 and 13. A sample chromosome is shown in Figure 4. As can be seen here, the dimension of a chromosome becomes 17.

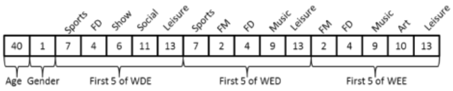

Figure 4. A sample chromosome from the population

Initial cluster centers are chosen randomly among the chromosomes. For each chromosome, the distance to each cluster center is calculated and the chromosome is assigned to the cluster with the nearest center. With the chromosomes assigned to the clusters, new cluster centers are calculated as

$$CC_i(x) = \frac{1}{n}\sum_{j=1}^{n} K_j(x) \tag{1}$$

where n is the number of chromosomes in the i^{th} cluster, K_j is the j^{th} chromosome in the i^{th} cluster, and CC_i is the cluster center of the i^{th} cluster.

The fitness function F_i of each cluster to be maximized is found as the inverse of the sum of the distances D_i of each cluster members to the center of that cluster. It can be formulated as

$$D_i = \sum_{j=1}^{n}\sum_{x=1}^{17}\left(K_j(x) - CC_i(x)\right)^2 \tag{2}$$

and

$$F_i = \frac{1}{D_i} \tag{3}$$

At this point, two cluster centers with a probability based on the fitness value of their clusters are selected as parents to produce offspring.

Offspring production starts with crossing over the parent chromosomes at a random point (Figure 5). After crossover, offspring are subjected to mutation with a low probability (1%) in order to prevent algorithm to be stuck in a local minimum. Then the parent chromosomes are replaced with the produced offspring. If there is any change in the cluster centers, the algorithm continues with forming the new cluster sets. If there is no change, it can be terminated.

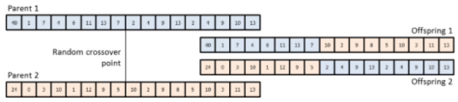

Figure 5. Crossing over two parents to produce offspring

In this work, in order to find the optimum number of clusters, the algorithm summarized below has been used [20].

For each chromosomes K_k, (k = 1, ...,P), a random number r_k is assigned, where P is the population size. This means the chromosome K_k consists of r_k data points and ($Kmax$ - r_k) do not cares, where $Kmax$ is the maximum number of the clusters.

Then the clusters are formed for each chromosome K_k, (k = 1, ...,P) by assigning data points to r_k clusters corresponding to the closest center. Cluster centroids are found as

$$z_i = \frac{1}{n_i}\sum_{X \in C_i} X \tag{4}$$

where n_i is the number of data points, X in cluster C_i.

The scatter within Ci for each chromosome K_k, (k = 1, ...,P)is calculated as

$$S_i = \frac{1}{n_i}\sum_{X \in C_i}\left\| X - z_i \right\| \tag{5}$$

and the distance between clusters C_i and C_j is

$$d_{ij} = \left\| z_i - z_j \right\| \tag{6}$$

The Davies–Bouldin (DB) index for each chromosome K_k, (k = 1, ...,P) is measured to find the fitness value

$$DB_k = \frac{1}{r_k} \sum_{i=1}^{r_k} \max_{j,\, j \neq i} \frac{s_i - s_j}{d_{ij}} \tag{7}$$

$$F_k = \frac{1}{DB_k} \tag{8}$$

After calculating the fitness values, chromosomes are undergone cross-over and mutation according to Roulette-Wheel of DB_k. Offspring are generated and replaced with old generation. This procedure is repeated with the new population and K_k with the best fitness is selected. Final number of clusters is equal to the number of data points in K_k.

2.3. ANN learning

Learning takes place after clustering. ANNs are chosen as the machine learning method and a separate ANN is constructed for each cluster. ANNs are trained by the standard backpropagation algorithm which uses the steepest-descent gradient approach to minimize the mean-squared error function [24].

The ANN inputs are the combination of explicit and implicit data: age, gender, time and available program genres at that time of concern. The output vector has 13 elements, each of them corresponding to a genre. The one that the user has watched has value 1 whereas the others are assigned as 0.

The ANNs are trained with 90% of the data collected by the HbbTV application for the respective cluster members. The 10% is allocated for testing only and never given to the networks during the training.

2.4. Program Recommendations

It may take days or even weeks for a user to get recommendations from the ANNs. It is because that the user has to watch at least 10 programs of the same genre in order her/his data to be included in the ANN learning and 90% and 10% of these data to be allocated for training and testing, respectively.

While waiting for the ANNs to finish their learning phase, the system uses the genre preferences information entered on the HbbTV registration screen by the user to make recommendations. Depending on user preferences for the time of concern, available programs are presented to the user.

Once ANNs have been successfully constructed in the learning phase, the system is ready to make program recommendations more closely to user's watching habits. The ANN output with the biggest value is considered as the recommended program genre for the corresponding inputs. As in the original work [1], the HbbTV application shows the recommendation list fetched from the server on the television screen (**Figure 6**).

3. Results

In the previous work of Topalli and Kilinc [1], gathering data by an HbbTV application was proven for a single user. Although it is possible to do it for multiple users, it has practical difficulties. In order to distribute the HbbTV information to multiple receivers, it should be added to the real DVB signal of the broadcaster which is beyond the focus of these studies.

Figure 6. Recommendations by the HbbTV application on the television screen [1]

Therefore some other approaches are taken to collect the data as if they come from the HbbTV application. In the previous work [1], a set of real television watching data recorded by eight people for one month consisting of date, time and genres watched were used as the implicit data. For the method proposed here, an online questionnaire is prepared and announced through several social media channels. Similar to the registration form of the HbbTV application (Fig. 3), participants are asked to fill their age, gender, and the top five genre preferences for three different times of the week to be used as the explicit data.

In total, 248 people responded to the questionnaire. The number of male participants (147 people, 59%) is slightly higher than the number of females (101 people, 41%). The age group 20 – 24 has the highest number of participants (58 people, 23%). “News” genre is the first choice in weekday evenings. The most preferred genre in weekend daytime and weekend evening is “Foreign Movie”.

3.1. GA clustering results

The number of clusters is calculated by the algorithm proposed by Bandyopadhyay and Maulik [20] and found as 11. The result of this clustering is given in Table1.

Table1. Cluster sizes after clustering by GA

Cluster	Number of Chromosomes
1	47
2	12
3	23
4	7
5	8
6	10
7	27
8	23
9	33
10	14
11	44
TOTAL	248

3.2. ANN learning results

In the original work [1], the learning data were program watching history recorded by eight people as if the HbbTV application collected them implicitly. A single ANN was trained and tested by these data since the number of users was not so big.

Now genre preference information for three different times of the week from 248 people is available and it is used to create the learning database as if these data came from the HbbTV application as the users were watching television programs.

The answers to the online questionnaire provide five input-output data per person per time. Obviously it is not enough to train the ANNs successfully. Therefore it is decided to generate more data using the questionnaire responses for each person participated.

The first choice of the user when all 13 genres are available would also mean that the user would make the same choice for all combinations of availability of 12 genres, provided that the first choice genre is always present. This yields to 2^{12} = 4096 alternatives. One of them is already given in the questionnaire, and the other 4095 data are generated by a script.

Similarly, the second choice of the user when her/his first choice is not available but other 12 genres are available would also mean that the user would make the same choice for all combinations of availability of 11 genres, provided that the first choice is not available and the second choice is present. This yields to 2^{11} = 2048 alternatives, 2047 of which are generated by a script.

Repeating the same procedure for the third, fourth, and the fifth choices, 7931 data are prepared per person without breaking the logic. Including participant's five choices, the total number of data per person per time slot becomes 7936 which makes a total of almost 6 million input/output samples for all users and time slots.

When a single ANN is used with the whole data set, it was not possible to get the network converged. Even after nine days of training, the epoch was still at six and the error was 8.53% with an average PC. This also shows the necessity of the clustering.

Eleven ANNs are constructed for the 11 clusters formed These ANNs are trained and tested with the data of people from respective clusters only. As in the original work [1], four-layer ANNs are used. The first and the second hidden layers have 30 neurons each, where the output layer has 13 neurons which is equal to the number of the genres. The learning parameter η is taken as 0.5, and the momentum term α as 0.9. Learning starts with random weights in [-0.5, 0.5] interval. The results are given in **Table 2**. Recommendation errors given in the table are calculated as the percentage of the number of incorrect recommendations with respect to the total number of recommendations [25].

Table 2.ANN learning results with clustered sets

ANN	People	Recommendation Error (%)
1	47	0.85
2	12	0.95
3	23	1.08
4	7	0.40
5	8	1.05
6	10	0.28
7	27	0.39
8	23	1.12
9	33	0.25
10	14	0.14
11	44	1.02
WEIGHTED AVG		0.73

4. Discussion and Conclusion

In this work, enhancements to the system given in [1] are proposed. In the original system, the HbbTV was utilized to collect program genres that users have watched and make recommendations in accordance with their watching habits. The ANN was the link between the collected data and program recommendations. There is no change here in the role of the HbbTV; but, the ANN learning has been improved by clustering the users with the GA.

Due to its nature, the proposed method should work well with the increasing number of users. Therefore a single ANN might not cope with the data coming from many users. To address this issue, the data of the users with similar features have been clustered into smaller subsets and a separate ANN has been created for each cluster.

Age, gender and five first program genre preferences for weekday evenings, weekend daytime and weekend evenings have been used for clustering. This new system has been tested with the data of 248 people. The optimum number of clusters is found as 11 by the used algorithm and these clusters have been formed by the GA. Then 11 ANNs have been trained and tested with the respective cluster data. With the improved approach proposed in this paper, digital broadcasters and operators can offer smart program recommendations to the owners of any HbbTV capable receivers without any software and hardware modification, and they can handle many users simultaneously in a better way.

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