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Learners Grouping in E-Learning Environment Using Evolutionary Fuzzy Clustering Approach

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Abstract—**Selection of appropriate learning objects and delivery of them to learners considering students' characteristics are known as a challenging task in e-learning systems. In design and development process of educational material, the attention must be focused on learner's characteristics and requirements which are defined in terms of content and learning style. To determine the best learning object, a model of learner can be constructed based on some learner's personal and behavioral features like learning styles, user's browsing history and user's prior knowledge. Grouping students based on their learning styles is one of appropriate approaches which have been followed in this area. However, some special characteristics and limitations of e-learning environments have led to the fact that any decision making and adaptation based only on static learning style recognition might be deficient. In this paper we introduce an evolutionary fuzzy clustering (EFC) method using genetic algorithm, in which learners are divided into some categories according to their behavioral factors and interactions with the system in order to adopt the most appropriate learning objects, methods, and recommendations. Results of the proposed method are compared with K-means and fuzzy C-means clustering methods using Davies-Bouldin cluster validity index and the comparison shows that EFC method has the better clustering performance than the others.**

Keywords-E-Learning System, Learning Style, Grouping, Fuzzy clustering, Evolutionary Methods.

I. INTRODUCTION

The recent applications of information technologies have a strong and social impact on the society and the daily life. One of the social aspectsthat has been transforming is the way of learning and teaching. In the recent years, we have seen exponential growth of Internet-based learning. E-learning is defined as the use of network technologyto design, deliver, select, administer and extend learning [1]. E-learning environment is a virtual-web based; in which learning takes place including administration, student information systems and the learning materials. The key feature of e-learning environments is their ability to provide a user-adapted presentation of the teaching material [2]. Adaptive systems build a model of the goals, preferences and knowledge of each individual user, and use this model throughout the interaction with the user, in order to adapt to the needs of him/her. Adaptive systems try to overcome this problem by using knowledge represented in the user model to adapt theinformation and links being presented to the given user. The educational systems were one of the first application areas for these systems [3]. A student in an adaptive educational system will be given a presentation that is adapted specifically to his/her characteristics [4].Adaptive educational system allows teacher to create and manage teaching units for sequential or free navigation[5]. Adaptive systems have been developed

to providing courses that fit the needs of learners [6].Adaptive presentation and curriculum sequencing technologies aim at tailoring the educational content to learner model (adapt the content or its sequencing)[7]. To provide the best learning object and deliver it to learner, consequently increase efficiency and effectiveness of the learning process, these systems should be able to adapt strategy based learner attributes[8]. In such systems, a model of student is built to provide personalized education which means the way each learner is trained and interacted will be different from the other learners. This model provides valuable information about learners such as their previous knowledge, learning capabilities, interests, learning style, and learning process. The main role of student model is to explain learners' behavior and personality so that the system can choose the most appropriate teaching strategy commensurate with their characteristics and requirements [9].

Brusilovskyidentified two different ways to build learner model [3]:

(i)Collaborative approach that askedlearners to provide explicitly information for building and updating the student model. For example, the learners can fill out questionnaires in order to identify their learning styles.

(ii) Automatic approach that build and update student model automatically based on the actions of the learners when they are using the learning system.

To adapt the behavior of system to learner's attributes and make the learner model the following critical issues should be focused [7]:

(i) The design of adaptation based on the learner information (what and how the system should recommend to learners with different attributes in terms of deciding which adaptation technologies could better serve the aims of the adaptation),

(ii) The selection of appropriate measures of learner's observable behavior which could serve as indicators of learner's attributes.

(iii) The qualitative analysis of these observable measures that could support the dynamic adaptation of the system during the interaction.

From this point of view, learners grouping is a task which categorizes learners such that the students who have a similar behavior (attribute) fall in a class (group). This process allows the teacher to determine and deliver most appropriate learning materials to learners in e-learning environment. The student information is recorded in Learning Management System (LMS) and this information is used to group learners.

Various methods have been proposed to make an automatic model of learner and to group learners. Some of them consider the attributes such as learning style, someone the domain knowledge, and so on [9]. Many researchers agree that considering learning styles increases the learning progress and makes learning easier for students. Since the learners have different ways of learning,when the learning style of a student does not match with the teaching style in an educational environment, learners may have problems in learning [10,11]. In web-based learning systems, more and more attention is paid on incorporating learning styles and providing courses that fit to the students' individual learning style. Some examples of such adaptive systems are CS383 [12], IDEAL [13], and INSPIRE [14].A central component of all approaches to identify the learning style of learner is the patterns of behavior, which represent either how students behave in the course or which performance they achieved on specific tasks in the course [15]. Incorporating the learning style information in the adaptive systems requires a learnersgrouping (categorizing) steps and/or selections (features/tools of the system that they access/use) as they interact with the system [7].

To group the learners one of the most used approaches is data mining techniques in order to discover the student's behavioral patterns. It helps in grouping them into some similar caregory to choose the most relevant and specific learning materials and strategies for each student category [16] .

On the other hand in many researches clustering algorithms were used to group learners (see Section 2). Fuzzy clustering, which uses fuzzy techniques to cluster the objects leads to clustering schemes that are compatible with everyday life experience as they handle the uncertainty of real data. Two main criteria are considered to measure the quality of clustering, compactness of clusters and their separation [17]. In the most widely used clustering algorithm, such as *K-means* and fuzzy *C-means*, the intra-class distance is minimized, therefore the compactness criterion is met only and the separation criterion not be considered [18].Since learner grouping can be seen as a clustering problem, in this paper we introduce an evolutionary fuzzy clustering (EFC) method to group learners in e-learning environment that defines an objective function so as the both compactness and separation criteria, considered in clustering problems, are met. We have evaluated functionality of proposed method on extracting students' groups from the underlying LMS logged data. Comparing the achieved categories and preferences obtained by the questionnaires traditionally used for learning style identification shows that the categorization accuracy is in a higher level for the most of dimensions of learning style. Such categorizations could use to design the adaptive behavior of an educational system and guide decisions about what the system should offer to learners with different styles and how to do it. The structure of paper is as follows: Section 2 reviews the literature on various clustering method that used in learner/user modeling. Some learning styles are introduced in Section 3. Section 4 describes the proposed evolutionary fuzzy clustering approach and evaluation of the proposed method and the experimental results are discussed in Section 5 and finally, the conclusion is given in Section 6.

II. Literature Review

As stated in previous section, data mining techniques are one of the most used methods to group learners in e-learning environment to extract knowledge from e-learning systems through the analysis of the information available in the form of data generated by their users [16]. Among these techniques, some clustering methods have been applied to group learners wherethere is not exit a desired group for each learner and aim is to discover and model the groups in which the learner are often grouped, according to some similarity measures.There exists a large number of clustering algorithm applications in e-learning environments and how to choose them depends on the particular application. For example, the clustering task was performed to learn patterns reflecting the student behavior and construct groups of learners with similar behavior to provide an efficient collaborative environment [16]. Since this paper proposes an evolutionary fuzzy clustering method, in the rest of this section we present a brief review on applied clustering methods in e-learning systems.

In [19], user actions associated to students' Webusage were gathered and preprocessed as part of a data mining process. The Expectation-Maximization (EM)algorithm was then used to group the users into clusters according to their behaviours. These results could be used by teachers to provide specialized recommendation to studentsbelonging to each cluster. The system administrators could also benefit from this acquired knowledge by adjusting the e-learning environment they manage according to it.

Carver, et.al. developed an adaptive system (CS383) based on the student's learning style that groipss the students using questionnaires.The response system of CS383 facilitates active, global, sensing, and intuitive learners. Active learners enjoy making choices and exploring the course material via their choices. Since most of the exam questions require the synthesis of multiple learning objectives, the student response system is an ideal learning component for global students to learn course information. Furthermore, the student response system supports: open-ended, short answer, concept questions and factual, true/false or multiple choice type questions. Depending on the type of question, both intuitive and sensing learners are addressed and categorized [12].Papanikolaou and Grigoriadou introduced an instructional framework which models the adaptive behavior of an adaptive educational hypermedia system by providing guidelines for planning the content, delivery and presentation of educational content to each individual learner [20]. Papanikolaou and Grigoriadou in another work, considered the critical issues influencing the adaptation mechanism based on the learning style information in an adaptive educational hypermedia system in[21]. In intelligent learning system proposed by Cha and his co-workers learners grouping hasbeen done by observing learner behavior patterns [23]. Graf and Kinshuk provided a basis for adaptivity by presenting a tool that enables learning management systems (LMS) to categorize students based on their behaviors during an online course [24]. They proposed an automatic student modeling approach for LMS for detecting learning style preferences based on Felder and Silverman learning style model [10]. Özpolat and Akar extracted the learner model based on Felder–Silverman learning style model using NBTree classification algorithm in conjunction with binary relevance classifier. So they could classify the learners based on their interests and their learning styles [9].

Mor and Minguillon proposed the use of clustering algorithms for grouping learners using information produced during learning process by the system such as user profile, navigational behavior, and academic results. They presented a framework to generate personalized itineraries for courses [25].
Castro et.al proposed a Generative Topographic Mapping (GTM) model to detect a typical behavior on the grouping structure of the learners. They introduced a clustering model to characterize groups of online learners using a constrained mixture of t distributions: the t-GTM, which simultaneously provides robust data clustering and visualization of the results [26]. They proposed other variants of GTM model in [27] to cluster and visualize logged data of the learners' behavior in an online course.

Furthermore, some recent works have been done on identifying learning styles with respect to the FSLSM automatically from the behaviour of students in learning systems as well as their performance on specific tasks. **García et al., built a model** for calculating learning styles based on data about patterns from students' behaviour and performance using Bayesian networks [28]. Graf and his co-workersapplied a rule-based method in order to calculate learning styles from the data of students' behaviour and performance [29].

Romero applied evolutionary algorithms to the usage data of the Moodle course management system to discover subgroups of learners. They aimed at obtaining fuzzy rules which describe associations between the learnersfinal mark and their interaction with the e-learning system [30]. Hogo used the fuzzy clustering techniques (FCM and KFCM) to find the learners profiles and classify them into specific categories based on their profiles[31].
From another point of view some researches have used the clustering techniques to group similar course documents, materials and other courseware resources such as [32, 33].

III. Learning Style and its Types

Many e-learning researchers have focused on developing e-learning systems with personalized learning processes to adaptively provide learning paths. To provide adaptive learning some learner's attributes (e.g. learning style, domain knowledge) should be considered [7].**Kolb [34]** and **Felder and Silverman[10]**indicated that students learn in many

different ways. Some learn by seeing and hearing, others by feeling and doing; some focus on acting. Thus, learning styles could be considered to develop a dynamic adaptive learning environment and matching the learner's requirements according her/his attributes, to assist her/him in finding the adaptivelearning objects efficiently [35]. Recognizing the behavior of individuals in a group or the collective behavior of the group and feeding this information back to the system can help the system to adapt its behavior to not only the individuals but also the average mood of the users. As learning styles are a significant factor contributing in learner progress, a challenging research goal is to attempt to represent specific characteristics of learners' learning style within Adaptive Educational Hypermedia Systems (AEHS). Learning style information can considerably contribute to the decision of the appropriate adaptation technologies for learners with particular profiles, as specific categorizations of learning styles seem to match better with specific adaptation technologies [7].

Sadler-Smith [36] identified four categories of 'learning style' to accommodate the range of aspects of individual differences referred in the educational psychology literature: (i) 'cognitive personality elements' such as field dependence and field independence [37], (ii) 'information-processing style' such as the experiential learning cycle [34] and the associated leaning styles (converger, diverger, accommodator, assimilator), or the related learning styles suggested by Honey & Mumford [38], activist, reflector, theorist, pragmatist, (iii) 'approaches to studying' such as deep approach, surface approach, strategic approach, lack of direction, academic self-confidence, (iv) 'instructional (i.e. learning) preferences' defined as an individual's propensity to choose or express a liking for a particular instructional technique or combination of techniques, such as dependent learners, collaborative learners, independent learners suggested by Riechmann&Grasha [38].

There are several learning styles in literature that associate specific characteristics to different categories oflearners and propose instruments and methods for assessing learning style.The most well-known learning style models are Myers–Briggs type indicator (MBTI) [39], Kolb's model [40], Felder and Silverman learning style model (FSLSM) [10], Herrmann Brain Dominance Instrument (HBDI) [40, 41], and Dunn and Dunn model [42].

Felder-Silverman learning style model (FSLSM) [10] seems to be most appropriate for the use in computer-based educational systems. Most other learning style models classify learners in few groups, whereas FSLSM describes the learning style of a learner in more detail, distinguishing between preferences on four dimensions.FSLSM is widely used in adaptive educational systems focusing on learning styles, so we select FSLSM for this research work which therefore makes this research widely applicable [6].

FSLSM consists of four dimensions in learning space: perception, input, processing and understanding. Perception dimension determines the type of information the student preferably perceive, learners are categorized as sensory or intuitive. Sensory learners like experiments, sights, sounds, physical sensations, and obvious facts but intuitive learners prefer theoretical information, abstracts, possibilities, insights, and so on. Input dimension determines kind of channel that learner receives information more effectively which consist of visual and verbal channels. A visual learner learns via visual materials such as pictures, diagrams, graphs and illustrations. Verbal learners remember better when they hear or read materials. They like listening texts or sounds. The information processing way by learners denotes the processing dimension. They may learn actively via experiments and with collaboration and engagement in physical activity or discussion. Reflective learners prefer to work alone, think about the information being presented to them and without trying things. The last dimension refers to the manner which learners understand through it. Sequential learners solve problems step by step in a linear reasoning process. Global learners make a global picture of the concept, make intuitive leaps, and then work with details. Table 1 shows the dimensions of the Felder's learning style and their scales [10].

In order to identify learning styles according to the FSLSM, the Index of Learning Styles (ILS) has been developed by Felder &Soloman in 1997. Each learner has a personal preference for each dimension.These preferences are expressed by values between 0 to +11per dimension. For example in the processing dimension,the value +11 means that a learner has a strong preferencefor active learning, whereas the value 0 states that a learnerhas a strong preference for reflective learning [43].

Table 1. Dimensions of Felder's learning style and their scales

Dimension	Scale
Perception	Sensitive / Intuitive
Input	Visual / Verbal
Processing	Active / Reflective
Understanding	Sequential / Global

IV. EVOLUTIONARY FUZZY CLUSTERING (EFC) METHOD

In clustering problems, a given data set is partitioned into clusters such that the similarity between points in same cluster is more than each other in different clusters [44]. Clustering problem always is an unsupervised problem and no predefined classes wouldn't show kind of desirable relation among the data [45]. *Fuzzy clustering* uses fuzzy techniques to cluster data and they consider that an object can be classified to more than one cluster. Fuzzy clustering procedures calculate group membership probabilities or degrees taking into account the distance between objects and group prototypes. This type of algorithms leads to clustering schemes that are compatible with everyday life experience as they handle the uncertainty of real data. The most important fuzzy clustering algorithm is *Fuzzy C-means (FCM)*. Dunn

[46] and Bezdek [47, 48] establish the fundamentals for fuzzy *C*-means clustering, which is the most broadly used fuzzy clustering algorithm. Two main criteria are considered to measure the quality of clustering, compactness of clusters and their separation. In the most widely used clustering algorithms, such as *K-means* and fuzzy *C-means*, the intra-class distance is minimized, therefore the compactness criterion is met only and the separation criterion not be considered [46]. While *C-means* clustering algorithm only considers the compactness of clusters, the evolutionary fuzzy clustering algorithm considers not only the compactness but also the separation. The objective function of EFC method consists of two parts, *Intra(K)* that is used for compactness and *Dens(K)* for separation. The purpose of this section is to define an objective function so as the both compactness and separation criteria are met. Genetic Algorithm(GA) has been used to optimize the objective function and find the center of clusters.

A. Compactness measure

***Defenition1**: Intra (K)*: it evaluates the average of all the distances between data points and centers, defined as

$$Intra(K) = \frac{1}{N}\sum_{k=1}^{K} u^q(C_k|Z_p)d(Z_p, C_k) \qquad (1)$$

where N is the number of data points, K is the number of clusters, Z_p is a data point, C_k is the center of cluster k, $d(Z_p, C_k)$ is an appropriate distance between Z_p and C_k, and $u(C_k|Z_p)$is the membership function defined by

$$u(C_k|Z_p) = \frac{\| Z_p - C_k \|^{-2/(q-1)}}{\sum_{l=1}^{K} \| Z_p - C_l \|^{-2/(q-1)}} \qquad (2)$$

where q is the fuzziness exponent with $q \geq 1$, increasing the value of q increases the fuzziness of algorithm. $u(C_k|Z_p)$is the membership value for the pattern Z_p in cluster k satisfying the following constraints:

1. $u(C_k|Z_p) \geq 0, \quad p = 1,\ldots,N, k = 1,\ldots,K$

2. $\sum_{k=1}^{K} u(C_k|Z_p) = 1, \quad p = 1,\ldots,N$

This membership function is defined such as in *C-means* [47].

B. Separation measure

Definition 2: $Dens(K)$**:** it evaluates the average density in the region among clusters in relation with the density of the clusters. The density among clusters must be significant low in comparison with the density in considered clusters. Therefore, the inter-cluster density is defined by:

$$Dens(K) = \frac{1}{K(K-1)} \sum_{k=1}^{K}\left[\sum_{\substack{j=1 \\ j\neq k}}^{K} \frac{density(b_{k,j})}{\max\{density(C_k), density(C_j)\}}\right] \qquad (3)$$

where $b_{k,j}$ is the middle point of the line segment defined by C_k and C_j and the term $density(C_k)$ is defined as:

$$density(C_k) = \sum_{p=1}^{n_k} u(C_k|Z_p) f(Z_p, C_k) \qquad (4)$$

where n_k is the total number of patterns in cluster C_k. The function $f(Z,b)$ is defined by

$$f(Z,b) = \begin{cases} 0 & if\ d(Z,b) > \sigma \\ 1 & otherwise \end{cases} \qquad (5)$$

and

$$\sigma = \frac{1}{K}\sqrt{\sum_{k=1}^{K} \| \sigma(C_k) \|} \qquad (6)$$

where $\sigma(C_k)$ is the variance of cluster C_k. Equ. (3) hasbeen proposed first by Halkidi and Vazirgiannis as a clustering validity index to measure the separation of the clusters [50]. Now we define the objective function as:

$$J(K) = \alpha Intra(K) + (1-\alpha) Dens(K) \qquad (7)$$

This definition indicates that both compactness and separation criteria is met. The first term in (7),Intra(K),indicates the average of all distances between each data point and centers. A small value of this term is an indication of compact clusters.Dens(K)indicates the average number of points between K clusters in relation with density within clusters. A small $Dens(K)$value indicates well-separated clusters [50]. Therefore the aim is the minimization of $J(K)$.

C. Applying genetic algorithm

To use genetic algorithm (GA) six fundamental issues must be determined: chromosome representation, the creation of the initial population, fitness function, selection function, the genetic operators making up the reproduction function, and termination criterion [51].

1. Chromosome representation

The representation scheme determines how the problem is structured in the GA and also determines

the genetic operators that are used. Floating point numbers, with values within the variables upper and lower bounds, have been used in this work. This representation is more efficient and produces better solutions for function optimization [52]. Each chromosome consists of $K \times n$ floating point numbers, representing K centers in R^n.

2. The creation of the initial population

The better choice of initial centers, in order to meet separation criterion, is to place them as much as possible far away from each other. Hence this procedure to choose the initial centers is performed:

Choose the first center at random
Repeat
for each data point in the remaining set compute the nearest center
choose a data point with largest distance to the nearest center as next initial center
Until the number of centers is less than *K*.

To create the initial population, this procedure must be repeated for *pop size* times.

3. Fitness function

In optimization problem, fitness function is the objective function of problem [42]. In this problem the fitness measure of each individual's evaluated according to (2)-(7).

4. Selection function

The selection of individuals to produce successive generation plays an extremely important role in the genetic algorithm. There are several schemes for the selection process: roulette wheel selection and its extensions, scaling techniques, tournament elitist models, and ranking methods [51]. In this research we have used ranking methods. These only require the evaluation function to map the solutions to partially ordered set, ranking methods assign P_i based on the rank of solution i when all solution are sorted. Normalized geometric ranking defines P_i for each individual by [53]:

$$P_i = q'(1-q)^{r-1} \tag{8}$$

Where q is the probability of selecting the best individual, $r$is the rank of the individual, where 1 is the best, and

$$q' = \frac{q}{1-(1-q)^{popsize}} \tag{9}$$

5. Genetic operators

The operators are used to create new solutions based on existing solutions in the population. Crossover and mutation are two basic types of operators. Crossover takes two individuals and produces two new individual and mutation alerts one individual to produce a single new solution. There are several mutation and crossover operators [52]. We use uniform mutation and arithmetic crossover. Uniform mutation randomly selects one variable, x_j, and sets it equal to a uniform random number $U(a_j, b_j)$:

$$x_i' = \begin{cases} U(a_i, b_i) & if \quad i = j \\ x_i & otherwise \end{cases} \tag{10}$$

where a_i and b_i are the lower and upper bounds, respectively, for each variable *i*. Arithmetic crossover produces two complimentary linear combinations of the parents:

$$\begin{aligned} X' &= r\overline{X} + (1-r)\overline{Y} \\ Y' &= (1-r)\overline{X} + r\overline{Y} \end{aligned} \tag{11}$$

where$r$ =*U(0,1)*, when *U(a,b)*is a uniform random number between *a*and b .

6. Termination criteria

The genetic algorithm moves from generation to generation selecting and reproduction parents until a termination criterion is met. The most frequently used stopping criterion is a specified maximum number of generations. Another termination strategy involves population converge criteria. In general, GA will force much of the entire population to converge to a single solution. When the sum of the deviation among individuals becomes smaller than some specified threshold, the algorithm can be terminated. The algorithm can be terminated due to a lack of improvement in the best solution over a specified number of generations. Several strategies can be used in conjunction with other [53].

The main steps of algorithm are provided below.

1) Initialize size of the population equal to *popsize* and create the start population $P(0)$ as described in (IV.C-2)

2) *t=1.*

3) Evaluate the fitness value of each individual in $P(t-1)$ and set $k = 1$.

4) Select two parents according to selection function and apply crossover to the selected parents with probability P_c, to create two individuals. Next, apply mutation with probability P_m to these individuals, then add resulting chromosome to the $P'(t)$.

5) $k = k + 2$. If $k < popsize$ go to step 4 otherwise go to step 6.

6) Apply evaluation operation and produce new generation.

7) $t = t + 1$.

Repeat steps (3-7) until termination criterion is met.

V. ANALYSIS OF EXPERIMENTAL RESULTS

To evaluate the proposed method, the results obtained from automatic students' grouping are analyzed considering the results obtained from the ILS questionnaire filled out by the students at the start of the online course. Calculating the ILS preference, each student is given a grade form 0 to 11 on each dimension of Felder's learning style. We have compared results of the ILS filled out by the students who were assigned to the same cluster in each dimension. To examine the impact of our algorithm we use it to divide learners in some groups in e-learning environment based on their behaviors logged in the system.In adaptive educational system, a critical issue for recognizing changes in learners' needs and preferences is to determinelearners' observable behaviour which are indicative of learners' learningstyle preferences.To do this, we have used logged data obtained from the underlying LMS, which includes students' interactions with the educational system. The features of the learners'behaviors we can record and measure generally depend on the functionality of the underlying web-based education system.In our system we aim at grouping students based on their activities while working with the system such as usingchat rooms, forums or type of learning materials they prefer andso on. These behaviors reflect the learning style of the learner. The most important learning style dimensions and correlated behavior have been shown in Table 2. The clustering task was performed to learn patterns reflecting the student's behaviors and construct groups of learners with similar behavior to provide an efficient collaborative environment.

Table 2.Behavioral factors considered for the clustering task

Dimension	Behavior Observed
Perception	Type of reading material (abstract, concrete)
	Type of slideshows
	Dedicating time for reading concepts and theories
	Dedicating time for reading examples and facts
	Doing additional exercises
	Reading additional examples
	Exam doing and revision time
Processing	Participation in forums
	Use of chat and mail systems
	Participation in collaborative/group tasks
	Choosing group or individual class projects
Input	Listening to lectures
	Using video materials
	Reading textual materials
	Type of slideshows
	Using diagrams and charts
Understanding	Pattern of access to the course materials
	Dedicating time for lessons' objectives and overviews

To evaluate the performance and accuracy of the proposed method, we conducted a study on 98 students who participated in an online undergraduate course named Fundamentals of Computer Networks. All kinds of learning materials, assignments, class projects and discussions could be embedded in this course and it may contain topics which have the potential to be discussed in forums, and web media which can be employed to extract the student'slearning style.We have carried out the experiment using*K*-means, *C*-means as most widely used clustering algorithmand EFC algorithms and then Davies Bouldin clustering validity index was calculated for them and a deep comparison over their results, performance, and their accuracy in grouping students have been done.Validity indices evaluate the goodness of clustering corresponding to a given value of *K*. In this paper we have used Davies-Bouldin cluster validity index. This index proposed by Davies and Bouldin and minimizes the average similarity between each cluster and the one most similar to it. The Davies-Bouldin index is defined as [54]:

$$DB = \frac{1}{K}\sum_{k=1}^{K} \max_{\substack{j=1,\dots,K \\ k \neq j}} \left(\frac{diam\left(C_k\right) + diam\left(C_j\right)}{dist\left(C_k, C_j\right)} \right) \tag{12}$$

where $diam(C)$ is the diameter of cluster, defined by:

$$diam(C) = \max_{u,w \in C} d(u,w) \tag{13}$$

The distance can be chosen as the traditional Euclidian metric for numeric feature. It is obvious that the smaller value of DB, the better matching in clustering.

The analysis results are discussed in the following subsection.

A. Results

To evaluate the proposed method, the numbers of clusters were set 3,4,5,6,7 and the clustering task is performed for each dimension separately. In *C-means* and EFC algorithm each data is assigned to cluster with greatest value of membership function and then the DB index is calculated for algorithms. These results have been shown in Fig. 1. As shown in this figure, for all these cluster numbers the EFC algorithm has the minimum value of DB index. It means that EFC algorithm has the better performance than the others. The minimum of DB index is reached at 4 (number of clusters) thus this amount was determined as the optimum number of the clusters in input dimension. Table 3 shows the clustering results of algorithms.

It can be seen that, the grade of learners which are in the same clusters is more similar in EFC method than the others. The clustering task is performed on activity data related to perception dimension. The DB index has been calculated for each algorithm and shown in Fig.2.As shown in this figure the DB index is minimized for K=4. Table 4 shows the results of clustering the students in perception dimension using 3 algorithms where the number of clusters has been set on 4. As indicated in Table 4, the achieved clusters in EFC method have learners with the same ILS grade.

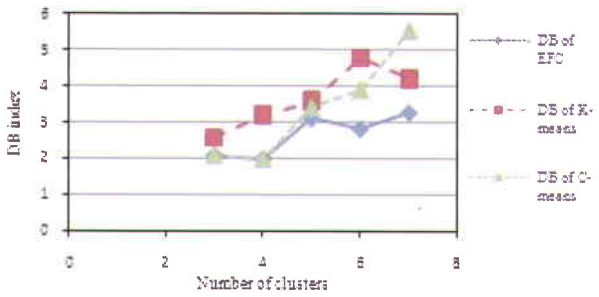

Fig 1. Davies-Bouldin index obtained by three algorithms for "input dimension"

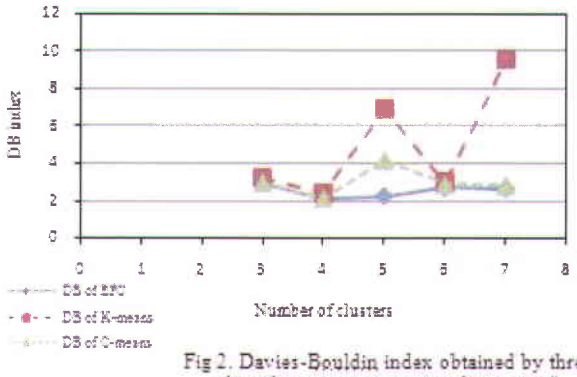

Fig 2. Davies-Bouldin index obtained by three algorithms for "perception dimension"

Table 3. The results of student's activities clustering based on"input dimension"

Cluster	Methods					
	EFC	n_k	*K*-means	n_k	*C*-means	n_k
Cluster 1	6,7,7,6,8,8,7,7,6,8,5,6,7 6,7,8,7,7,6,4,5,7,7,7 7,8,8,7,7,5,7,7,7,6	34	6,7,8,6,7,7,7,7,8 1,1,2,1,1,1,2,9,10 9,9,11,3,4,5,2,3,5,3	28	6,8,1,2,1,1,10,4,5,7,11,11 9,3,4,5,1,2,10,9,11 8,5,7,9,10,6,4	28
Cluster 2	1,1,1,1,1,1,2,3,1 1,2,0,1,2,2,1,2,3	18	7,7,6,7,8,7,7,7 1,1,1,11,11,10 9,9,4,3,3,5,5,4,5	23	7,7,8,9,3,3,6,7,7,1,1,1 7,5,2,5,4,7,6,7,2,0,8,10	24
Cluster 3	9,11,11,11,8,9,10,10 10,11,9,10,9,9,10,9 11,9,9,9,11,10,10	23	8,5,4,7,5,6,1,3,2,2,3 9,11,10,11,9,9 11,3,5,4,5,4,5	24	7,6,7,1,2,9,11,3,2,7,8 9,4,3,6,9,11,9,4,5,6,6,7	23
Cluster 4	4,6,3,5,3,3,4,4,5,5 3,4,5,5,4,2,5,5,3,4,5,5,3	23	7,6,8,6,8,6,5,7,7,7,7 1,2,0,8,9,10,10,10,10,6,5,4	23	7,1,9,5,7,7,10,5,5,8,5,4 3,3,11,3,5,8,7,1,10,10,5	23

Table 4. The results of student's activities clustering based on "perception dimension"

Cluster	Methods					
	EFC	n_k	*K*-means	n_k	*C*-means	n_k
Cluster 1	3,5,5,5,4,5,4,7,5,5,5 6,4,6,5,3,3,4,5,4,3,4 6,3,4,5,6,3,3,3,5	31	5,5,4,5,3,5,4,10,8,9,8,10, 0,2,0,2,2,2,8,6,8,8,8,7	24	5,4,9,2,8,8,10,10,9,11, 10,0,7,9,7,6,7,6,6,5, 4,4,2,2,7,8	26
Cluster 2	10,10,9,10,8,10,10,10, 10, 9, 9, 9, 9, 9, 10, 9, 9, 8,9,9, 11, 10,11,10,10	25	5,5,3,10,10,10,9,9,10,9,9, 11,11,10,0,2,3,0,2,0,3,7,7,9,7,7	26	5,10,0,8,7,5,5,3,10,10, 9,0,0,7,7,3,4,2,2,8,9,8	22
Cluster 3	0,2,1,0,2,2,2, 3,2,0,2,0,2,2,2,2,2,0,2,3	20	7,5,3,3,4,5,6,3,3,5, 10,9,9,9,10,8,7,6,6	19	5,3,8,10,0,2,2,2,6,8,9,11, 3,3,3,3,9,9,10,5,9,10,9,1,2,7	26
Cluster 4	7,8,7,9,8,7,7,9,8,8, 6,8,7,7,7,6,8,6,8,7,8,7	22	3,4,5,5,6,4,6,3,4,4,6,9,10, 10,9,2,1,2,2,2,2,2,8,7,9,8,7,7,8	26	4,5,8,9,2,2,7,5,3,5,5,10, 9,8,3,4,6,6,3,4,6,10,2,7	24

The same steps are performed on activity data related to understanding dimension. The values of DB index have been shown in Fig 3. As shown in this figure the index has been minimized for *K=4* and the EFC algorithm has the minimum DB index value for each number of clusterswhich means that this method has the best performance. The clustering results for the "understanding dimension"have been presented in Table 5 and the number of clusters is 4.

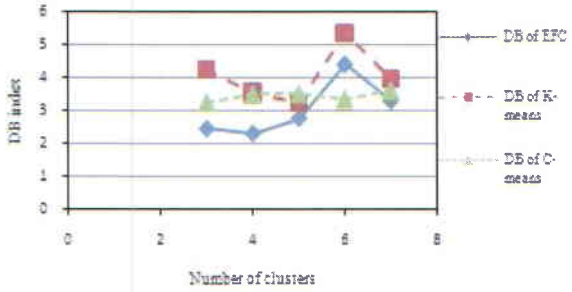

Fig 3. Davies-Bouldin index obtained by three Algorithms for "understanding dimension"

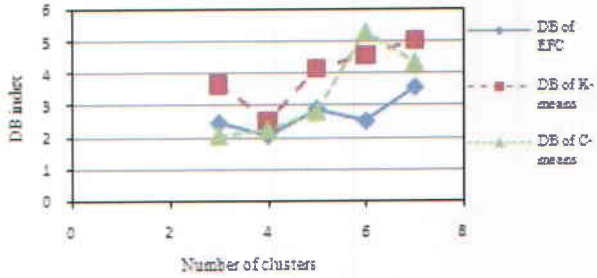

Fig 4. Davies-Bouldin index obtained by three algorithms for" processing dimension"

Table 5. The results of student's activities clustering based on "understanding dimension"

Cluster	Methods					
	EFC	n_k	*K*-means	n_k	*C*-means	n_k
Cluster 1	11,8,9,9,10,11,11, 9,11,8,8,10,8,9,8,8,8, 8,8,10,10,9,10	23	11,11,8,10,9,1,6,5,7,7, 6, 5,7,6,4, 5,5,5,2,3,3	21	11,1,7,3,8,2,9,1,6, 7,4,7,2,3,3,2,10,1,7,5,3	21
Cluster 2	1,2,1,1,0,1,0,0, 0,1,0,0,0,2,1,1,2,1,1,1	20	8,8,8,8,2,0,1,0,0,2,1,1, 1,6,6,4,5,3,5,4,4,5	22	8,9,7,6,5,5,5,3, 0,2,1,1,5,9,10,1,0,2,7, 4,2,3,10,11,8,0,1,6,6,4	30
Cluster 3	6,6,6,6,7,7,6,7, 8,5,5,7,5,7,7,7,6,5,8,7, 7,6,4,7,5,4,7,5,6,5,7	31	9,11,9,9,8,10,1,1,0,2,1, 6,7,7,5,7,4,7,4,2,2,3,3,3,2	25	10,6,5,6,5,8,8,1, 6,5,4,9,8,1,7,5, 9,8,10,7,8,7,5,2,3	25
Cluster 4	5,4,5,2,4,5,5,3, 2,4,3,5, ,2,4,3,4,5,3,3, 3,3,3,2	24	9,10,11,8,10,8,8,10,1,0, 0,0,1,6,7,6,8,5,7,8,7,7,7, 5,5,2,5,3,4,3	30	11,7,4,2,8,1,0,0, 6,4,3,4,5,11,8,0, 0,8,5,7,7,5	22

Table 6. The results of student's activities clustering based on "understanding dimension"

Cluster	Methods					
	EFC	n_k	*K*-means	n_k	*C*-means	n_k
Cluster 1	5,7,7,8,8,5,5,8,7,6,4,7,8, 5,7,8,6,7,6,7,7,8,7,5, 7,6,6,9,5,8,5,7	32	5,8,5,7,7,7,7,6,9,3,0,2,11,9, 10,11,10,11,5,5,5,4,3,4	24	3,4,7,6,4,5,4,2,4,6,5,2,1, 9,4,5,8,9,11,4,5	21
Cluster 2	2,1,0,3,2,0,2,2,0,1 ,2,0, 2,1,2	15	8,5,7,8,7,6,5,0,2,2,2,0,1,2, 10,10,10,10,8,9,9,4,4,5,4,2,5,3,4,2	30	5,7,9,10,11,5,3,5,8,0, 2,8,4,8,7,8,7,10,5,7,9,8,2,3	24
Cluster 3	9,11,10,10,10,11,7,10, 9,10,9,9,0,11,8,9,10, 9,10,10,9,8,8,11, 9	25	7,7,5,8,4,7,8,6,6,5,7,7,2,1,0, 1,10,9,9,8,4,5,4	23	8,5,7,6,0,2,11,10,5,4,8,0, 2,2,9,4,3,7,7,0,10,2,4	23
Cluster 4	2,4,3,4,4,5,3,5,4,2,2,5,5, 5,5,3,4,4,3,4,4,4,5,4,2,4	26	6,8,5,8,2,9,11,7,9,9,10, 10,8,2,3,4,3,2,5,4,4	21	7,7,9,11,5,7,5,2,1,10,10,10,10, 9,2,5,7,5,6,1,9,8,4,6,8,2,9,10,3,4	30

Totally, clustering task has performed on activity data related to processing dimension. Fig.4 shows the values of DB index and clustering results have been summarized in Table 6. Comparing the values of DB index, we can state that the EFC algorithm has the better performance than the other ones, and the optimum number of clusters is 4.

Totally, as shown through this section, for each dimension of FSLSM learning style, the EFC approach grouped learners in clusters that have the most similar ILS grade and so EFC had the minimum value of DB index particularly for the optimum number of clusters. This means that the EFC can perform the clustering task better than *K*-means and *C*-means.

Comparing DB index value of algorithms (figures 1-4), EFC has the better performance than *K*-means and *C*-means, specially when number of clusters is great and for optimum number of clusters, too. It means EFC has the better clustering results according to clustering goodness factors. Also by considering cluster members ILS grad (tables 1-4), it can be seen the learners ILS grad which are in the same cluster is more similar in EFC than other methods. It means that EFC groups learners better than *K*-means and *C*-means according to ILS grad criteria.

Comparing the runtime of these methods, a major point will be apparent on this subject. As the EFC is involved with some calculations to find the center of clusters, it takes more time, while clustering task is performed, compared with *K*-means and *C*-means. But as clustering was performed and the center of clusters were found, data (learners) are clustered more compactness and separate. So if achieved clusters have been used to find most appropriate clusters for a new learner, the result is better than other methods. But if we want to group learners in a real time

application, EFC has the low performance and this is the disadvantage of EFC method.

VI. Conclusion

In this paper, we introduced anevolutionary fuzzy clustering (EFC) algorithm to group students in an online educational system to make a model of students based on some of their behavioral factors and interactions with the system. In addition, since there are some relationships and dependencies among these behavioral features, we divided the features into four groups according to their associations with the dimensions of Felder's learning style model. To evaluate performance and accuracy of the proposed method, we conducted a study on 98students participated in an online undergraduate course. In the proposed approach, the learners grouping is done employing *K*-means, *C*-means and EFC algorithms. Having compared clustering accuracy of the algorithms together, we observed that EFC algorithm has more precision and more accuracy in putting students into some groups according to their behavior which logged in LMS. It formed clusters in such a way that the members have high similarity in their learning style. Assigning students to clusters properly helps system provide more personalized content and learning recommendations.

In future research works, we would like to use the EFC method to group learners appropriately and recommend them the proper material according to each cluster that they belong to it. We plan to use this method in online course and design an adaptive educational system. The effectiveness and/or efficiency of adaption approach will be measured through subjective estimation of learner's performance, learning time, navigation patterns. The disadvantage of this methodis its high computational and memory usage costs. To improve disadvantage of method we would like to use another optimization method such as Particle Swarm Optimization (PSO).

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