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Abstract A learning style describes the attitudes and behaviors, which determine an individual's preferred way of learning. Learning styles are particularly important in educational settings since they may help students and tutors become more self-aware of their strengths and weaknesses as learners. The traditional way to identify learning styles is using a test or questionnaire. Despite being reliable, these instruments present some problems that hinder the learning style identification. Some of these problems include students' lack of motivation to fill out a questionnaire and lack of self-awareness of their learning preferences. Thus, over the last years, several approaches have been proposed for automatically detecting learning styles, which aim to solve these problems. In this work, we review and analyze current trends in the field of automatic detection of learning styles. We present the results of our analysis and discuss some limitations, implications and research gaps that can be helpful to researchers working in the field of learning styles.

Keywords Learning styles · User model · Educational systems

1 Introduction

Students acquire and process information based on their learning styles (Felder and Silverman 1988). There are many learning style definitions, but one widely accepted by leading theorists is the one given in Keefe (1979) which states that: "[a learning style is] the composite of characteristic cognitive, affective, and psychological factors that serve as relatively stable indicators of how a learner perceives, interacts with, and responds to the learning environment". Learning styles are described in learning style models, which are defined by theorists in the fields of psychology and cognitive science. A learning style model classifies students according to where they fit on a number of scales belonging to the ways in which they receive

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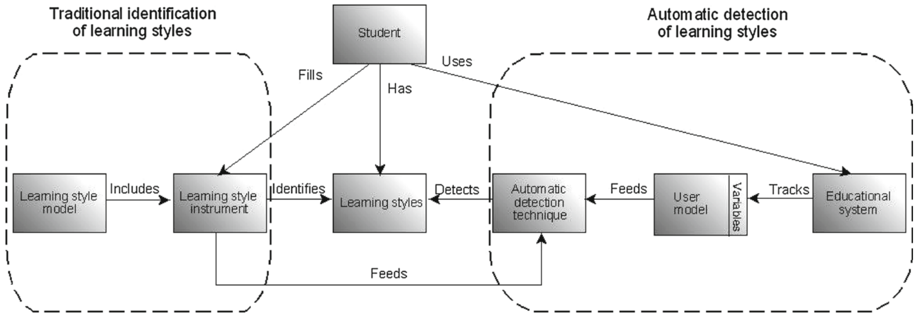

Fig. 1 Identification of learning styles and automatic detection of learning styles

and process information (Felder and Silverman 1988). A great interest in the field of learning styles over the last 20 years has led to the proliferation of models. Thus, Coffield et al. (2004) identified 71 learning style models which are worth considering. Generally, these models were produced by groups of researchers working in isolation from each other. Thus, there exists a certain degree of overlap between learning style models regarding their dimensions, proposed learning styles, and terminology. However, a learning style construct is a valuable description that helps students to understand how their learning process works. Learning styles also allow educational practitioners and instructional designers to adapt their teaching styles and educational material to their students' learning styles. Then, learning style identification is important because it helps to improve learning performance, enhance motivation, increase enjoyment, and reduce the learning time (Popescu 2009).

The traditional way to identify learning styles is through a questionnaire that students are asked to fill out (see Fig. 1). While these instruments present good reliability and validity, they have been subjected to some criticism. Firstly, filling out a questionnaire is a boring task that requires an additional amount of work from the students, given that some questionnaires have more than 100 items. Secondly, students may tend to choose answers arbitrarily if they are not aware of the importance or the future uses of the questionnaire. Thirdly, students can be influenced by the way the questionnaire is formulated, which may lead them to give answers perceived as more appropriate. Fourthly, questionnaires assume that students are aware of their learning preferences, but this is not always the case. Finally, learning styles can vary over time. A questionnaire is a static approach, as soon as the learning style changes, the results of the questionnaire are no longer valid.

To solve these limitations, several approaches for automatically detecting learning styles have been proposed (García et al. 2007; Yannibelli et al. 2006; Villaverde et al. 2006; Cha et al. 2006a; Popescu 2009; Graf and Kinshuk 2010; Latham et al. 2012). Research in the field of automatic detection of learning styles is particularly important in educational systems that adapt learning material to students' preferences. The automatic detection of learning styles has several advantages over traditional approaches. Since information is gathered from the students' interaction with the educational system, no supplementary amount of work—such as answering a questionnaire or providing explicit feedback about learning preferences—is required from the students. In addition, the automatic approach gathers information from a time span rather than from a specific point in time. Therefore, changes in the students' learning characteristics can be followed over time. In addition, an automatic approach that uses real data to detect students' learning styles has the potential to be more accurate and less error-prone. Finally, an automatic approach allows students to focus on learning, instead of making them waste time answering questionnaires or providing feedback.

Figure 1 shows a schematic view of the process of automatic detection of learning styles. This process consists in building a user model that describes students' learning preferences while using an educational system. Thus, students' behavior is tracked by the educational system and collected in the user model. Then, an automatic detection technique is applied. This technique is initially trained with the user model and the results of the learning style identification instrument obtained from a group of initial students. After the training, the automatic detection technique is able to classify new students using their user model.

In this context, our goal is to present the state of the art and current trends in the field of automatic detection of learning styles. Although other surveys have addressed the use of learning styles (they have done it from another perspective such as the adaptation of learning material (Akbulut and Cardak 2012) or the analysis of learning style models (Deborah et al. 2012)), a review of the automatic detection of learning styles has not been conducted in the current literature. Hence, in this work, we analyzed several approaches for automatically detecting learning styles from different perspectives according to the components shown in Fig. 1. Thus, in Sect. 2, we enumerate what *learning style models* were used, along with the *models' dimensions* and the *instrument* used for identifying students' learning styles. In Sect. 3, we analyze the proposed *automatic detection techniques* used for detecting learning styles. In Sect. 4, we describe what *information* was used to create the user model and the *variables* for predicting learning style preferences. In Sect. 5, we identify some common experimental settings, such as the *educational systems* used for tracking students' behavior and the *type of users* that participated in the experiments. In Sect. 6, we highlight the main results, findings and contributions of the approaches analyzed. In Sect. 7, we clarify the *type of research* (theoretical/experimental) carried out. Finally, in Sect. 8 we discuss some open issues in the field of automatic detection of learning styles and present our conclusions.

2 Learning style models

A learning style model classifies students according to where they fit on a number of scales pertaining to the ways they receive and process information (Felder and Silverman 1988). These models specify a small number of dimensions that collectively provide a good basis for designing effective instruction (Felder 2010). Additionally, a learning style model is associated with an instrument that allows educational practitioners to identify the learning style preferences of students.

In the field of automatic detection of learning styles, the model plays a central role, guiding researchers during that process. In addition, an instrument is commonly used to evaluate the performance of the automatic detection approach. Therefore, in the next sections, we introduce the core ideas of each learning style model used for automatically detecting learning styles. Also, we briefly explain the dimensions and learning styles described by these models. Finally, we outline the instruments associated with the learning style models.

2.1 Kolb

Kolb's learning style model is based on the Experiential Learning Theory (Kolb 1984). This theory describes a learning process through which concrete experience is followed by reflection and observation, leading to the formulation of abstract concepts and generalizations, the implications of which are tested in new situations through active experimentation. This four-stage cycled process is the foundation of Kolb's model, which defines the following learning styles:

- *Accommodating*: this learning style describes students that like doing things actively, learning by doing, trial-and-error, carrying out plans and experiments, and becoming involved in new experiences. Accommodating students also enjoy working with other people.
- *Diverging*: diverging students like viewing concrete situations in many different perspectives. They are interested in people and tend to be feeling-oriented.
- *Converging*: converging students like finding practical applications for ideas, problem solving and decision making. They prefer dealing with technical problems rather than interpersonal issues.
- *Assimilating*: assimilating students like inductive reasoning and assimilating disparate observations into an integrated explanation. They like abstract ideas and concepts, and create theoretical models. They are also more concerned with theories than with people.

Kolb also created an instrument called Learning Style Inventory (LSI) designed to help learners understand the process of experiential learning and their unique individual style of learning from experience. Five versions of the LSI have been published over the last 35 years. All versions have had the same format: a short 12 item questionnaire that asks respondents to rank four sentence endings that correspond to the four learning styles.

We found that Kolb's model was only applied by Georgiou and Makry (2004). In that work, the authors present an algorithm based on fuzzy-neural networks to automatically detect the four learning styles of Kolb's model. Besides, as they did not carry out any experimentation, the proposed approach was not evaluated empirically, so the LSI instrument was not used. In particular, we think that Kolb's model was applied in some early works in the field of automatic detection of learning styles. However, current trends tend to use other models, such as Felder's model or customized models, which fit better within educational systems.

2.2 Gardner

Another model used in the context of automatic detection of learning styles is Gardner's theory of Multiple Intelligences (Gardner 1993). It provides a framework that recognizes several intelligences and suggests that people use one or two to maximize their personal learning. Gardner identified 8 intelligences:

- *Logical/Mathematical*: this intelligence involves skill in calculations as well as logical reasoning and problem solving. People strong in this intelligence are usually described as being "smart".
- *Linguistic*: this intelligence involves the ability to use words effectively for reading, writing, listening and speaking. This intelligence is important for providing explanations, descriptions and expressiveness.
- *Spatial*: this intelligence includes the ability to perceive the visual world accurately and to perform transformations and modifications on one's initial perceptions via mental imagery.
- *Musical*: this intelligence includes sensitivity to pitch, rhythm, timbre and emotional aspects to sound.
- *Kinesthetic*: this intelligence highlights the ability to use one's body in highly skilled ways for both expressive (e.g. dance, acting) and goal-directed activities (e.g. athletics, working with one's hands).
- *Naturalist*: a person with this intelligence displays empathy, recognition and understanding for living and natural things.
- *Interpersonal*: this intelligence emphasizes self-knowledge, goal setting, self-monitoring/correction, and emotional self-management.

– *Intrapersonal*: this intelligence involves understanding other people. It includes the ability to recognize the emotions, moods, perspectives and motivations of people.

The Multiple Intelligences Developmental Assessment Scales (MIDAS) provides a method for obtaining a descriptive understanding of a person's multiple intelligences profile. The MIDAS questionnaire inquires about an extensive list of skills, involvements and enthusiasms. This instrument includes 119 questions, each of which has to be answered by selecting from among six descriptive statements.

We found that Gardner's model was only used in Kelly and Tangney (2006). In that article, the authors explore the logical/mathematical, linguistic and spatial intelligences "as they reflect the abilities that are historically designated as intelligences" (Kelly and Tangney 2006). The musical intelligence was also taken into account because of its emotive power. The MIDAS instrument was administered to students with a twofold purpose. First, the questionnaire was used to determine which intelligences had greater learning performance. Second, to evaluate the proposed approach, some students were given resources based on the analysis of the MIDAS instrument, while others were given resources according to their detected intelligences.

Although we have considered intelligences and learning styles equally, some differences can be drawn. Intelligences refer to things one can do, are unipolar and value directional. In contrast, learning styles refer to how one prefers to do things, are bipolar and value differentiated. Thus, learning styles have been used in educational systems to automatically adapt learning material according to detected learning preferences. In contrast, intelligences can be used to identify students' prior knowledge and evaluate students' learning gain.

2.3 Felder

This model is based on Kolb and Myers-Briggs ideas. Felder states that the learning process can be improved if educators' teaching styles are matched to students' learning styles. In Felder's model (Felder and Silverman 1988), learners are characterized by values in four dimensions that describe how the students' learning process works. Felder's model has been widely used in educational systems mostly because it provides an instrument that allows educational practitioners to quantify students' learning style preferences.

Felder's model has four dimensions (each of which defines two opposite learning styles):

– *Processing*: this dimension describes the way perceived information is converted into knowledge. The learning styles of this dimension are:
  - *Active*: active learners do not learn much in situations that require them to be passive. They work well in groups and tend to be experimentalists.
  - *Reflective*: reflective learners do not learn much in situations that provide no opportunity to think about the information being presented. They work better by themselves or with at most one other person and tend to be theoreticians.
– *Perception*: this dimension relates to the type of information a student prefers to perceive. The learning styles of this dimension are:
  - *Sensitive*: sensors like facts, data, and experimentation. They like solving problems by standard methods and dislike "surprises". They are patient with detail but do not like complications. Sensors are good at memorizing facts and are careful but may be slow.

  - *Intuitive*: intuitors prefer principles and theories. They like innovation and dislike repetition. They are bored by detail and welcome complications. Intuitors are good at grasping new concepts and are quick but may be careless.

- *Input*: this dimension considers the way in which learners prefer to receive external information. The learning styles of this dimension are:

  - *Visual*: visual learners remember best what they see: pictures, diagrams, flow charts, time lines, films, demonstrations.
  - *Verbal*: verbal learners remember much of what they hear and more of what they hear and then say.

- *Understanding*: this dimension describes the way students progress towards understanding. The learning styles of this dimension are:

  - *Sequential*: sequential learners follow linear reasoning processes when solving problems and can work with material when they understand it partially or superficially.
  - *Global*: global learners make intuitive leaps and may be unable to explain how they came up with solutions. They may also have great difficulty understanding partial information.

The Index of Learning Styles (ILS) is used for identifying learning style preferences in Felder's model. This instrument is a 44-item questionnaire proposed in Felder and Soloman (1997). The questionnaire has 11 items for each dimension and each item has two mutually exclusive options. Thus, students' learning style preferences are expressed by values between -11 and $+11$ per dimension. If a student's score on the scale is between -3 and $+3$, he/she is fairly well balanced on the two learning styles of the dimension. Otherwise, the student has a moderate/strong preference for one learning style of the dimension (Felder and Spurlin 2005).

Felder's learning style model is the most referenced framework in the field of automatic detection of learning styles. Seventy percent of the works surveyed employed Felder's model. Almost all of them automatically detected the learning styles of the four dimensions. However, some dimensions were not considered in some articles. For example, in Crockett et al. (2011) experiments were undertaken with the perception and understanding dimensions, but no reasons were given by the authors for not considering the other dimensions of the model. In turn, in Carver Jr et al. (1999); Zatarain-Cabada et al. (2010a,b) the processing dimension was ignored because it was considered that hypermedia courses and electronic learning implicitly address the needs of active and reflective students. Finally, in García et al. (2007, 2008), Villaverde et al. (2006) and Yannibelli et al. (2006) the input dimension was not detected because their educational system did not provide videos and simulations.

Regarding the ILS instrument, we found that it was used for addressing two different goals. On the one hand, some works used the instrument to initialize the user model, such as in Alkhuraiji et al. (2011), Carmona et al. (2008), Zatarain-Cabada et al. (2009, 2010a,b) and Sangineto et al. (2008). This initialization is usually optional, which means the student can choose not to complete the questionnaire. However, filling out the questionnaire allows the educational system to adapt lessons from the start of the learning session. On the other hand, the ILS instrument was used for evaluating the performance of the automatic detection approach, such as in Bousbia et al. (2010), Cha et al. (2006a,b), Crockett et al. (2011), Dung and Florea (2012), García et al. (2007, 2008), Graf et al. (2008, 2009), Latham et al. (2012), Özpolat and Akar (2009) and Sanders and Bergasa-Suso (2010). The evaluation is straightforward, since it consists in comparing the learning styles automatically detected with the ones identified by the instrument.

In addition, other works did not use any instrument to identify the students' learning styles, such as Carver Jr et al. (1999); Kolekar et al. (2010); Villaverde et al. (2006) and Yannibelli et al. (2006). These works are characterized by taking a theoretical perspective of the problem, introducing new approaches to address the automatic detection of learning styles without conducting empirical evaluations or otherwise evaluating the proposed approach with simulated data.

2.4 Biggs

Biggs' model (Biggs 1987) analyzes students' approaches to learning. Basically, an approach to learning describes what students do when they go about learning and why they do it. Biggs identified 3 approaches to learning used by students:

– *Surface*: the main purpose of this approach is to meet requirements minimally; a balance between working too hard and failing.
– *Deep*: students that use this approach study to actualize interest and competence in particular academic subjects.
– *Achieving*: it is based on competition and ego-enhancement, obtain highest grades whether or not material is interesting.

Educational practitioners use the Biggs Inventory Learning Style (BILS) to identify students' approaches. BILS helps to gain clearer insight into how students go about their studies and how they perceive their own learning. This instrument consists of a list of statements on study strategies, motives and attitudes. The BILS includes 120 statements concerning higher education studies and studying. Students must indicate to what extent each statement applies to them, expressing their view by circling a number on a scale from 1 to 5.

Like Kolb's model, Biggs' model is not frequently used in the field of automatic detection of learning styles, and it is only referenced in Stathacopoulou et al. (2005). In that work, the surface and deep approaches of Biggs' model were automatically detected. The proposed automatic detection technique did not detect the achieving approach, and no reasons were given for ignoring it. Regarding the BILS instrument, it was used to identify students' learning approaches and evaluate the performance of the automatic detection technique. We think that few educational researchers have applied Biggs' model because it describes the learning process in little depth. This model also classifies students in fixed categories rather than consider learning preferences as tendencies.

2.5 Custom models

Custom models incorporate characteristics from one or several traditional learning style models. By taking into account well-known learning style models, custom models are able to include a large number of learning preferences without increasing students' workload. Thus, custom models address issues such as the multitude of learning style models, the concept overlapping and the relations between learning style dimensions. Custom models are easy to extend in order to incorporate new learning dimensions. However, they are characterized by a lack of theoretical support since they are not defined by learning style theorists.

From our literature review, 5 of the 27 works surveyed employed a custom model. In Chang et al. (2009), the students were classified according to 3 learning styles: *dilatory* students take more time to browse a learning unit, often reviewing the same unit and skipping it; *transitory* students spend the least amount of time in browsing, have the least browsing depth, and their browsing order is irregular; *persistent* students have the highest browsing depth, and their browsing order is regular. However, no information is given about which learning style model these learning styles are based on. Nevertheless, some similarities can be found between these learning styles and Biggs' model, as *transitory* seems to be related to Biggs' *surface* learning style, and *persistent* to Biggs' *deep* learning style. In turn, in Gilbert and Han (1999) and Lo and Shu (2005) the custom model used defines 3 learning styles: *auditory*, *visual* and *tactile/kinesthetic,* which can be related to Gardner's *musical*, *spatial* and *kinesthetic* intelligences. Finally, in Popescu (2009) and Stash et al. (2006) the proposed custom models are based on widely known learning style models. Thus, in Popescu's custom model the dimensions "visual/verbal", "serial/holistic" and "active/reflective" were taken from Felder, the dimension "abstract/concrete" was taken from Kolb, "individual/team" from Dunn and Dunn (Dunn and Griggs 2003), and "careful/not careful" was included as a characterizing trait that many learning style models posses. In turn, in Stash et al. (2006), a custom model was defined in which the dimension "active/reflective" was taken from Felder, "field dependent/field independent" from Witkin (Witkin et al. 1977), and the dimensions "verbalizer/imager" and "holist/analytic" from Riding (Riding and Rayner 1998).

The instrument used to identify learning styles in custom models depends on which models the custom model is based on. Thus, for the custom model defined in Gilbert and Han (1999) and Lo and Shu (2005), the MIDAS instrument can be used. Regarding the custom models defined in Popescu (2009) and Stash et al. (2006), the dimensions taken from Felder's model can be identified with the ILS instrument, the dimensions taken from Kolb's model can be identified with the LSI instrument, and so on.

3 Automatic detection techniques

A number of artificial intelligence (AI) techniques have been proposed to automatically detect students' learning styles. In this section, we describe how these techniques can be classified and which are currently been used.

In Graf (2007), two main approaches of automatic detection of learning styles were identified: data-driven and literature-based. The data-driven approach aims at building a classifier that imitates a learning style instrument. The automatic detection of learning styles in data-driven approaches is carried out by an AI classification algorithm that takes the user model as input and returns the students' learning style preferences as output. This approach has the advantage that it uses real data to classify the user, so it can be very accurate. However, the approach strictly depends on the available data and therefore, a representative dataset is crucial to build an accurate classifier. This classifier has to be able to identify learning styles from data of the same learning course and at the same time identify learning styles from data of any other course.

On the other hand, the literature-based approach uses the user model to get hints about students' learning style preferences and then apply a simple rule-based method to calculate those preferences from the number of matching hints. This approach is similar to the method used for calculating learning style preferences by the learning style instruments. The literature-based approach has the advantage that it is generic and applicable to data gathered from any learning course because learning style models are developed for learning in general. However, the approach might have problems in estimating the importance of the different hints used for calculating the learning style preferences.

Six of the works surveyed (Carver Jr et al. 1999; Dung and Florea 2012; Graf et al. 2008, 2009; Latham et al. 2012; Popescu 2009; Sangineto et al. 2008) used a literature-based approach, whereas the rest used a data-driven approach. We think that the data-driven approach is more commonly used than the literature-based approach because the latter requires having some knowledge of psychology and cognitive science to correctly estimate the importance of the hints. In contrast, data-driven approaches are more familiar to computer science researchers because they require gathering relevant information for the user model and then use an AI classification algorithm to automatically detect the learning style preferences.

The works that employ a data-driven approach apply several AI classification algorithms to automatically detect learning styles. In the next sections, we review which AI techniques are used in the detection process.

3.1 Bayesian networks

Bayesian networks are a compact, expressive representation of uncertain relationships among parameters in a domain. They are modeled as a directed acyclic graph that represents a probability distribution, where nodes represent random variables and arcs represent probabilistic correlation or dependency between variables (Charniak 1991). The strengths of the dependencies are given by probability values. For each node, a probability table specifies the probability of each possible state of the node given each possible combination of states of its parent. These tables are known as conditional probability tables (CPT).

In our literature review, we found that bayesian networks are one of the most widely adopted classifiers. Bayesian networks were used in Alkhuraiji et al. (2011), Carmona et al. (2008), García et al. (2007, 2008), Ahmad and Shamsuddin (2010) and Kelly and Tangney (2006). The reported reasons to use a bayesian network are its natural representation of probabilistic information, its efficiency, and its support to encode uncertain expert knowledge.

Two steps are needed to build a bayesian network. First, the structure of the network must be defined (qualitative model). Then, the network's parameters (quantitative model) must be set (Brusilovsky and Millán 2007). Figure 2 shows an example of the structure of a bayesian network, where leaf nodes represent student's observable behavior (see Sect. 4.2) and root nodes represent the learning styles to infer. The structure of the network can be elicited from data or can be defined by an expert or someone with thorough knowledge of the domain. All the articles surveyed used the latter approach. As it is mentioned in Kjærulff and Madsen (2008), defining the network structure through expert knowledge is a simpler and straight approach, especially when there are few variables involved.

Finally, once the structure of the network is defined, the CPT must be set. Similarly to the structure definition, two approaches can be used to set the network parameters: through

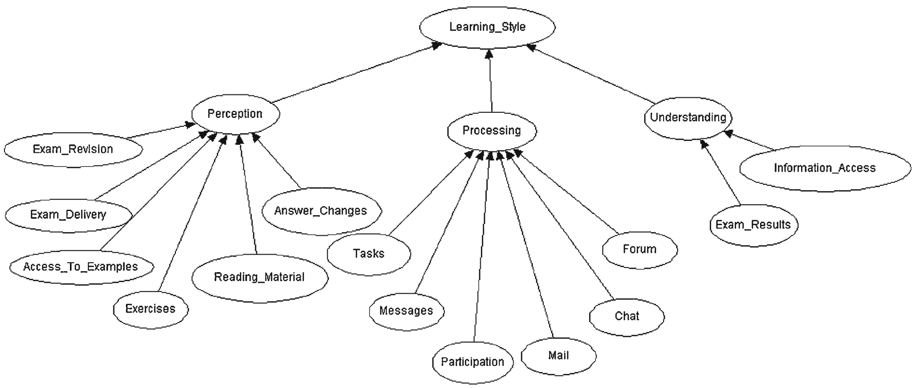

Fig. 2 Bayesian network model (from García et al. 2007)

expert knowledge (García et al. 2007, 2008; Carmona et al. 2008) or learning the parameters from data (Ahmad and Shamsuddin 2010; Alkhuraiji et al. 2011; Kelly and Tangney 2006).

3.2 Decision trees

Decision trees are a classifier method able to produce models that can be comprehensible by human experts (Breiman et al. 1984). Decision trees algorithms have two-phases, namely building phase and pruning phase. In the former, the training dataset is recursively partitioned until all the instances in a partition belong to the same class. During the latter, the nodes are pruned to prevent overfitting and to get a tree with higher accuracy (Symeonidis 2005).

Decision trees are an AI classification algorithm frequently used in the field of automatic detection of learning styles. This algorithm is employed because of its simplicity, the rules of the classification are visible and easy to understand, and it is appropriate when many attributes are relevant. Decision trees were used in Cha et al. (2006a,b), Crockett et al. (2011), Ahmad and Shamsuddin (2010) and Özpolat and Akar (2009).

The structure of a decision tree consist of a root node which represents the attribute that is selected as the base to build the tree, the internal nodes which represent attributes that reside in the inner part of the tree, and leaves which represent the classes to infer. Branches between nodes represent possible values for the attribute the branch initiates (Symeonidis 2005). Figure 3 shows an example of the structure of a decision tree, where leaves represent the learning styles to be inferred, and the nodes represent the features tracked that lead to those learning styles.

There are many algorithms that can be used to classify students according to their learning style when using decision trees. Some of these algorithms are ID3, C4.5, J48, NBTree and RandomTree (Witten and Frank 2005), which vary according to the order in which the attributes are selected and the splitting criterion use to build the tree. In this context, in Ahmad and Shamsuddin (2010) the authors used C4.5, J48, NBTree and RandomTree to infer the learning styles of the students. In turn, Özpolat and Akar (2009) applied ID3, C4.5, NB and NBTree whereas Cha et al. (2006a,b) do not mention which algorithm was used. It is worth noticing that neither Ahmad and Shamsuddin (2010) nor Cha et al. (2006a,b)

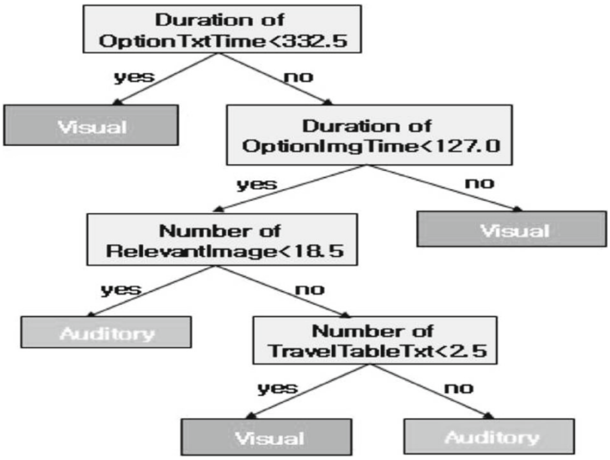

Fig. 3 Decision tree model (from Cha et al. 2006b)

explained the rationale for choosing a particular algorithm, which may indicate that it was chosen based on a trial-and-error basis. Only Özpolat and Akar (2009) supports the selection of the NBTree algorithm, claiming it is appropriate when many attributes are relevant and they are not necessarily independent.

3.3 Neural networks

Neural networks are computational models based on the biological neural structure of the brain. Roughly speaking, a neural network is a set of connected input/output units, where each connection has a weight associated with it. During the learning phase, the network learns by adjusting the weights so as to be able to predict the correct class label of the input tuples (Han et al. 2006).

Similarly to bayesian networks and decision trees, neural networks are commonly used in the automatic detection of learning styles. Thus, neural networks were used in Georgiou and Makry (2004), Kolekar et al. (2010), Lo and Shu (2005), Stathacopoulou et al. (2005), Zatarain-Cabada et al. (2009, 2010a,b) and Villaverde et al. (2006). The reported reasons for using a neural network are its speed of execution, and its ability to be updated quickly with extra parameters and to generalize and learn from specific examples.

The structure of a neural network consist of three layers: the *input layer* contains neurons that receive signals from the environment, the *hidden layer* contains neurons that receive their input from other neurons and transmits its outcome to others, and the *output layer* that contains neurons that send their output to the environment. The structure of a neural network can be mapped easily to the problem domain. As it is shown in Fig. 4, a neural network for detecting the learning style of students has: an input layer with a neuron for each student's behavior tracked, a hidden layer with neurons that provides the processing power of the network, and an output layer with one neuron for each learning style detected. However, defining the number of neurons of the hidden layers is a complex task, and although there are some empirical rules for determining the desirable number of neurons, there are no theoretical rules for determining the optimal number (Lo and Shu 2005; Villaverde

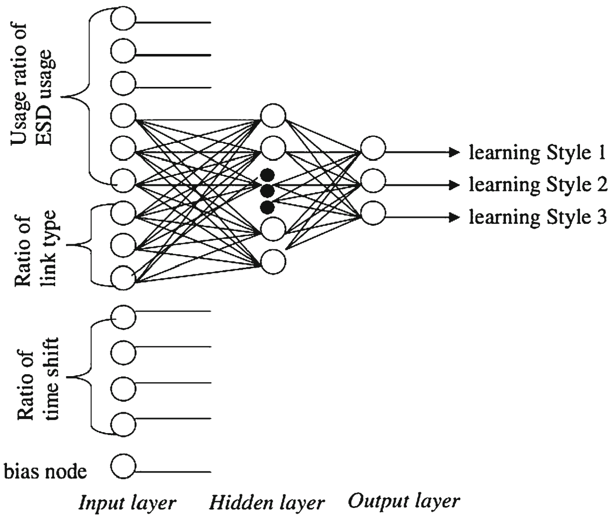

Fig. 4 Neural network model (from Lo and Shu 2005)

et al. 2006). Thus, all the works surveyed set this architectural parameter via trial-and-error experimentation.

Neural networks have also been combined with fuzzy logic in order to detect the learning styles of the students, such as in Stathacopoulou et al. (2005) and Zatarain-Cabada et al. (2009, 2010a,b). Fuzzy logic provides a mode of qualitative reasoning, which is closer to human decision making (Stathacopoulou et al. 2005). A fuzzification and defuzzification layer must be defined on a fuzzy-neural network. During the fuzzification stage, fuzzy rules are applied, whereas in the defuzzification, the fuzzy assessments are weighted to generate the output. Stathacopoulou et al. (2005) report that fuzzy-neural networks are capable of handling uncertainty better than other computing methods, however, further research is needed since current works are small-scale studies.

3.4 Other AI techniques

In this section, we review other AI techniques that are not so commonly used in the automatic detection of learning. In Cha et al. (2006b), the authors used *hidden Markov networks* (HMM) to infer students' learning styles. HMM is a statistical method that uses probability measures to model sequential data represented by sequence of observations (Cha et al. 2006b). In contrast to other AI techniques like decision trees, HMM considers the sequence of students' actions, which is useful for tracking the progress in the users' behavior.

In turn, in Yannibelli et al. (2006) and Chang et al. (2009) *genetic algorithms* were applied. A genetic algorithm is an adaptive heuristic search algorithm inspired by Darwin's theory of evolution, where candidate solutions evolve toward better ones (Yannibelli et al. 2006). To apply a genetic algorithm for automatically detecting learning styles a group of chromosomes should be defined where each gen is associated with a student's action, and new populations of chromosomes are generated that best describe the student's learning styles. Chang et al. (2009) also used *genetic algorithms* with *K-NN* to classify students according to their learning styles. K-NN represents every sample in a n-dimensional space, where n denotes the students' behaviors tracked. Thus, two students are considered to have the same learning style if their distance is shorter than that of other students that posses other learning preferences.

In Gilbert and Han (1999), the authors used *case-base reasoning* to classify students according to their learning styles. The case-based reasoning approach consists in matching new cases to previously observed ones. Thus, two students are considered to have the same learning styles is they exhibit the same behavior while solving problems planned by an educational system.

Finally, *a graphical probabilistic model* was used in Sanders and Bergasa-Suso (2010). Their approach is similar to K-NN, since students' actions were plotted in a n-dimensional space, where students that were near to each other were considered to have the same learning styles.

4 User model

A user model is a description of someone containing the most important or interesting facts about him or her (Schiaffino and Amandi 2009). The content of a user model can be explicitly provided by the user, or it has to be learned using some intelligent technique. In this section, we analyze which type of information can be used to model the user's behavior to detect his/her learning styles. Also, we present some variables that can be used to build the user model according to the learning styles' dimensions.

4.1 User model information

In the context of educational systems, the user profile or student model is used for guiding students in their learning process according to their knowledge and learning styles (García et al. 2007).

In Popescu (2009), two modeling methods used in educational systems were identified: *explicit* and *implicit*. *Explicit* modeling was used in early educational systems, where a learning style instrument was used for diagnostic purposes. The main advantage of this method is its simplicity: the system only has to use the results of the questionnaire to infer the learning style preferences. However, this approach has many disadvantages that were mentioned in Sect. 1.

On the other hand, an implicit modeling method is a dynamic approach that observes students' behavior to detect learning style preferences. An implicit modeling method does not suffer from the disadvantages of explicit modeling, but it is harder to implement since it requires determining which observable behavior to track in order to get enough reliable information to build a robust student model. In this context, all the works we analyzed applied an implicit modeling method because it allows educational systems to automatically detect learning styles.

Implicit modeling methods can be classified into three groups (Popescu 2009), according to which kind of information is used to infer learning style preferences and update the user model:

- *Performance*: this method consists in analyzing the performance of the students when using the educational system. A good performance is interpreted as an indication of a style that matches the one currently being used in the course, while a bad performance is interpreted as a mismatched learning style and it triggers a change in the current learner model.
- *Feedback*: in this method the system asks the students to provide feedback on the learning process experienced so far, and adjusts the learner model accordingly.
- *Behavior*: this method consists in analyzing the students' behavior (e.g. browsing pattern, time spent on a course, type of resources used, etc) and consequently inferring a corresponding learning style.

The distribution of implicit modeling methods employed in the works surveyed are as follows: four works analyzed students' performance (Alkhuraiji et al. 2011; Zatarain-Cabada et al. 2009, 2010a,b; Gilbert and Han 1999); only one analyzed students' feedback (Carmona et al. 2008); one did not specify the method used (Georgiou and Makry 2004); and twenty one analyzed students' behavior. We think that the widespread use of educational systems, such as Moodle [1] and custom educational systems, have facilitated the automatic detection of learning styles based on the analysis of students' behavior. We claim that this is due to the fact that educational systems provide a rich set of features that may be mapped to different learning styles. Therefore, online course contents such as text, images, audios, videos, forums, chats and wikis provide a good framework to explore students' learning preferences.

4.2 Variables of the user model

As we mentioned previously, an implicit modeling method usually consists in tracking students' behavior to build the user model. In the context of automatic detection of learning styles, a user model has a number of variables for each student trait being tracked. The number and type of variables that can be tracked in an educational system vary according to

[1] https://moodle.org/

the functionality that the environment provides. For instance, the Moodle environment provides an out-of-the-box track mechanism for logging students' usage of forum, chat, mail, exercises, tests and learning material.

We found that the number of variables used for building the user model ranges from two (Dung and Florea 2012) to more than one hundred (Popescu 2009). A greater number of variables is expected to imply a higher precision in the automatic detection of learning styles (Popescu 2009), given that a user model with many variables implies describing the students' behavior in more detail. However, a great number of variables entails that the educational system must provide large quantities of learning material in order to cope with all the variables tracked.

The type of variables that can be tracked in a educational system can be classified as (Stathacopoulou et al. 2005):

– *Knowledge*: such as the number of correct, incorrect or almost correct answers in a test.
– *Chronometric*: such as the time spent to read the material, the time to find the correct answers in a test, the total time on a task.
– *Try*: such as the number of attempts to find the correct solution, the number of times a subject has been reviewed.
– *Navigation*: such as the number of times a topic has been selected, the number of times the student moves to another topic.

The four types of variables previously enumerated were used in García et al. (2008), Graf et al. (2009), Ahmad and Shamsuddin (2010), Kelly and Tangney (2006), Lo and Shu (2005), Sanders and Bergasa-Suso (2010) and Popescu (2009). Some of the variables included in these works were: exam results, results a learner achieved on each kind of question (*knowledge*); time dedicated to exam revision, time it takes the student to finish and submit the exam, time spent on textual content (*chronometric*); number of exercises done, number of examples read, number of visits of textual content (*try*); participation in forums, use of chat and mail systems, content skipped (*navigation*). Besides, some works only used one or two types of variables. Thus, knowledge variables were used in Crockett et al. (2011) and Latham et al. (2012), such as practical and theoretical questions correctly answered. Chronometric variables were used in Chang et al. (2009), Dung and Florea (2012) and Stathacopoulou et al. (2005), such as time spent on each learning object, and time the student moved the mouse over a button. In turn, navigation variables were used in Bousbia et al. (2010), Carver Jr et al. (1999), Cha et al. (2006a,b), Chang et al. (2009) and Özpolat and Akar (2009), such as back and next button clicked, and type of learning content acceded.

Finally, it is important to know which variables of the user model can be used to detect every learning style. Thus, in Graf et al. (2009), Popescu (2009) and Latham et al. (2012) several variables that can be tracked in educational systems were identified to detect Felder's learning styles. Next, we summarize some variables that can be used to detect the learning style of Felder's model:

– *Active*: number of questions answered, number of times a learner answers the same question wrong twice, and number of performed exercises.
– *Reflective*: number of visited learning content, time spent on learning content, and number of visits in a forum.
– *Sensing*: number of right answers given after seeing an example, number of correctly answered questions about details, and number of times a student revised his/her answer before submission.

- *Intuitive*: number of right answers given after a theoretical explanation, number of correctly answered questions about concepts, number of correctly answered questions about developing new solutions.
- *Visual*: number of right answers given after seeing an image, number of images clicked, and time spent watching videos.
- *Verbal*: number of right answers given after reading text, number of visits in a forum, and time spent in the forum.
- *Sequential*: number of times the student chooses to be guided through the steps of solving a problem, and number of correctly answered questions about details.
- *Global*: number of times the student chooses to solve a problem straight away, number of visited outlines, and time spent on outlines.

5 Educational systems

In this section, we analyze the educational systems used for automatically detecting learning styles and the type of users that interact with those system to get their learning style detected. Several terms have been used in the literature to refer to these environments, such as adaptive educational hypermedia system, educational hypermedia system, web-based educational system, web-based instruction system, learning management system, intelligent tutoring system, adaptive learning system, adaptive educational system, and e-learning system, among others. In this literature review, we use the term educational system in its broadest sense, namely an environment that encompasses all types of systems associated with education. We have also classified the educational systems used to automatically detect learning styles in three categories:

- Learning management system (LMS): a LMS provides a set of features to support teachers in the construction, administration and management of courses. They treat all learners equally, regardless of their learning style preferences. LMS focuses on the presentation of educational material.
- Intelligent tutoring system (ITS): this kind of system focuses on the use of techniques from the field of AI to provide broader and better support for the learners (Graf 2007). Its main goal is to help students to solve problems.
- Adaptive educational hypermedia system (AEHS): its focus is to provide hypermedia content that fits the user characteristics. The system should satisfy three criteria: it should be a hypertext or hypermedia system, it should have a user model, and it should be able to adapt the hypermedia using this model (Brusilovsky 1996).

We found that 37 % of the works surveyed used an adaptive educational hypermedia system: CS383 (Carver Jr et al. 1999), CREDITS (Cha et al. 2006a,b), POLCA (Dung and Florea 2012). Arthur (Gilbert and Han 1999), DeLeS (Graf et al. 2008, 2009), EDUCE (Kelly and Tangney 2006), WELSA (Popescu 2009), iLessons (Sanders and Bergasa-Suso 2010), IWT (Sangineto et al. 2008) and AHA! (Stash et al. 2006). Intelligent tutoring systems were used in 15 % of the works analyzed: OSCAR (Crockett et al. 2011; Latham et al. 2012) and Zamna (Zatarain-Cabada et al. 2009, 2010a,b). In turn, 15 % used a learning management system (Bousbia et al. 2010; Chang et al. 2009; García et al. 2007, 2008; Lo and Shu 2005). In addition, 30 % of the works did not use any type of educational system as the proposed approach was evaluated with simulated data or no evaluation was done (Alkhuraiji et al. 2011; Carmona et al. 2008; Georgiou and Makry 2004; Ahmad and Shamsuddin 2010; Kolekar et al. 2010; Stathacopoulou et al. 2005; Villaverde et al.

2006; Yannibelli et al. 2006). Also, only one work (Özpolat and Akar 2009) used a web search engine. Finally, it is worth noticing that all but one of the educational systems used for automatically detecting learning styles were custom made, DeLeS (Graf et al. 2008, 2009) being the only tool developed as an add-on to the Moodle learning management system.

As mentioned previously, users have to interact with an educational system for their learning styles to be automatically detected. Educational systems can be used by a wide range of users ranging from primary school students to undergraduate students, teachers and employees. Thus, the following type of users have taken an online learning course to automatically detect their learning styles: elementary students (Chang et al. 2009), high school students (Zatarain-Cabada et al. 2010a,b; Kelly and Tangney 2006), university students (Bousbia et al. 2010; Crockett et al. 2011; Dung and Florea 2012; García et al. 2007, 2008; Graf et al. 2008, 2009; Latham et al. 2012; Lo and Shu 2005; Özpolat and Akar 2009; Popescu 2009; Sanders and Bergasa-Suso 2010; Stash et al. 2006), teachers (Zatarain-Cabada et al. 2009) and employees (Sangineto et al. 2008). In addition, in Ahmad and Shamsuddin (2010), Stathacopoulou et al. (2005), Villaverde et al. (2006) and Yannibelli et al. (2006) no educational system was used, since the proposed approach was evaluated using simulated data. Curiously, all the university students that participated in the experiments were computer science students. This can be explained as the works surveyed were performed by computer science researchers who can easily test their approaches in class. Besides, since most of the works surveyed applied Felder's model, which has been widely used in engineering education, it is reasonable to expect researchers to test their approaches with engineering-related learners. Finally, these facts also explain why little research has been conducted in elementary and high school.

6 Results

In this section, we enumerate the main results and findings of the works surveyed. We concentrate on experimental works and report the performance of the proposed approaches for automatically detecting learning styles. These results are not meant to be used as a comparison between different approaches, since they are based on different data, but they serve as an insight of the performance of the automatic detection of learning styles and highlight its feasibility. Thus, in Fig. 5 we show the precision achieved by the approaches that automatically detect Felder's learning styles, since it is the model most widely referenced. As can be seen, the processing dimension was detected with a precision that ranged from 61 % (García et al. 2007, 2008) to 81 % (Sanders and Bergasa-Suso 2010). Regarding the perception dimension, the precision ranged from 40 % (Sanders and Bergasa-Suso 2010) to 100 % (Yannibelli et al. 2006). The input dimension was detected with a precision that ranged from 53 % (Özpolat and Akar 2009) to 100 % (Cha et al. 2006a,b). Finally, the precision achieved in the detection of the understanding dimension ranged from 66 % (Dung and Florea 2012) to 100 % (Yannibelli et al. 2006).

Furthermore, other experimental works reported the accuracy of the proposed approach without specifying the precision on each dimension. As Fig. 6 shows, the accuracy achieved using Felder's model ranged from 69 % (Villaverde et al. 2006) to 94 % (Ahmad and Shamsuddin 2010). Also, an accuracy of 87 % (Chang et al. 2009) and 90 % (Lo and Shu 2005) was obtained using custom models. In turn, the only work that used Biggs' model achieved an accuracy of 90 % (Stathacopoulou et al. 2005).

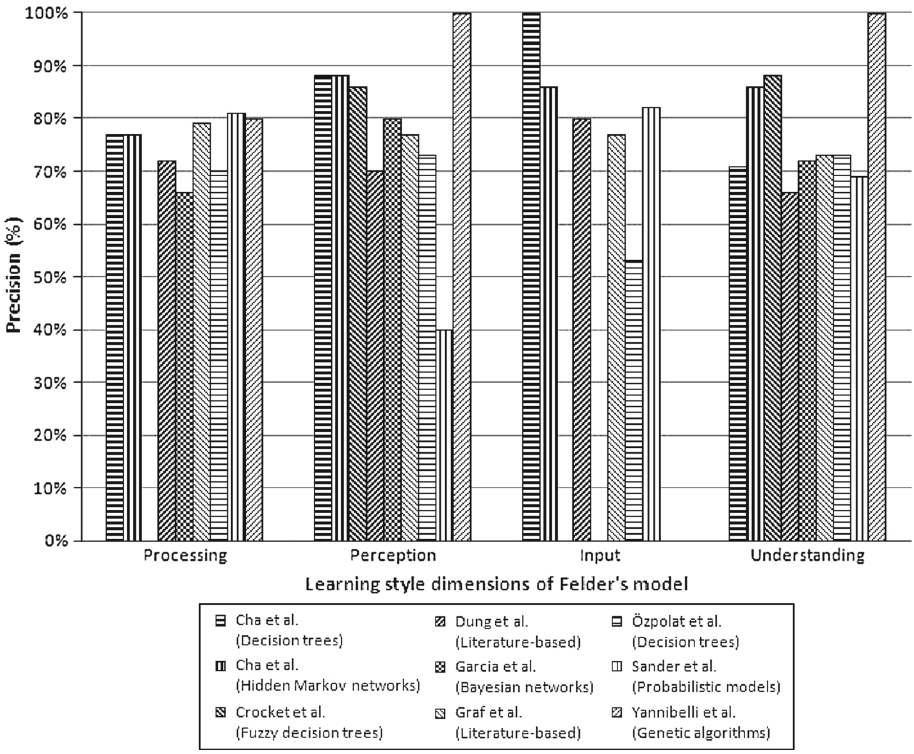

Fig. 5 Precision of automatic detection of learning styles using Felder's model

7 Research type

We classify the research type of the works analyzed into two groups:

- *Theoretical*: in this kind of works, the authors present a new framework or approach that is characterized by the lack of experiments or empirical evaluations. Generally these articles describe a first approach that will be extended in future works.
- *Experimental*: experimental works evaluate the proposed approach through empirical evaluations. In general, the experimental settings consist of a learning style instrument, an educational system where the proposed approach is tested, and the users that interact with the system.

Not surprisingly, of the 27 works analyzed only 5 (19 %) were theoretical research, and 22 (81 %) were experimental. In our view, this is due to the small number of resources needed to perform the experiments and the widespread use of educational systems.

8 Discussion

In this section, we present our conclusions and discuss some limitations and open issues in the field of automatic detection of learning styles. Since learning style models are a core component in the field of automatic detection of learning styles, learning style models' open issues influence directly the automatic detection approaches. For this reason, we begin our

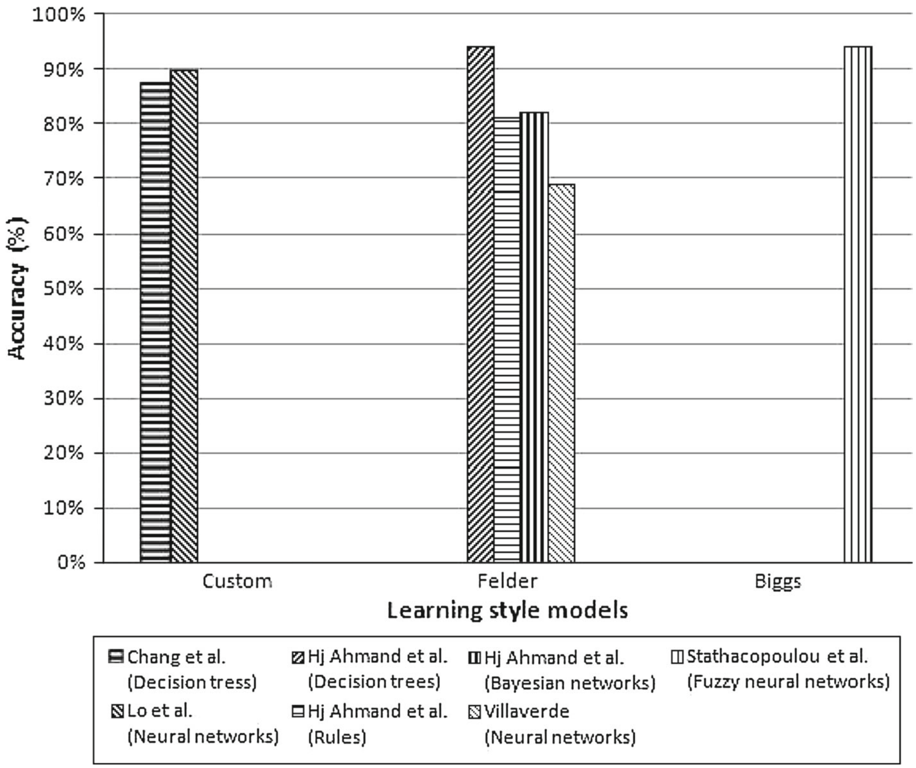

Fig. 6 Accuracy of automatic detection of learning styles

discussion by pointing out some open issues in the area of learning style models. Next, we discuss the adoption of learning style models in the field of automatic detection of learning styles. Finally, we mention some open issues and research gaps in the field of automatic detection of learning styles.

8.1 Learning styles models: open issues

There has been a lot of research in the field of learning styles over the last 20 years. However, a controversial issue that remains open is the overlapping learning style models proposed in the literature. Thus, competing ideas about learning have led to a proliferation of terms and concepts, many of which are used interchangeably in the learning style literature (Coffield et al. 2004). This hinders the adoption of a learning style model, as it is difficult for educational practitioners to know which model is the most relevant and which one they should use. While some learning style theorists attach little importance to which learning style model is used since the instructional approaches of the models are essentially identical (Felder 1996), others claim that learning style models differ in their design, implications for pedagogy and evidence on pedagogical impact (Coffield et al. 2004). Furthermore, the relationships and similarities among learning style models are still unclear. Thus, an agreement among leading learning style theorists could clarify an otherwise fragmented and isolated research area.

8.2 Learning style models in the field of automatic detection of learning styles

In the work of Coffield et al. (2004), 71 learning style models were identified, and 13 of them were categorized as major models according to their theoretical importance, their widespread use and their influence on other models. In the field of automatic detection of learning styles we found that researchers have opted for learning style models derived from major ones, such as Felder model or custom models. We think that these models have proven to be suitable for use in educational systems and exhibit a good degree of validity and internal consistency. In particular, Felder's model has been widely used because it provides a questionnaire capable of quantifying students' learning style preferences. This allows researchers to evaluate the automatically detected learning styles on a fine-grained basis, such as strong, moderate or mild. Other reasons to employ Felder's model are that it is suitable for use with an educational system (Carver Jr et al. 1999), that it has been widely tested in engineering education, and that it considers learning styles not as fixed traits but as differential preferences for learning.

8.3 Automatic detection of learning styles: open issues

One major criticism in the field of automatic detection of learning styles is that it is characterized by a very large number of small-scale applications of particular models to small samples of students in specific contexts (Coffield et al. 2004). In this vein, population sizes used for automatically detecting learning styles are significantly small: 27 (Bousbia et al. 2010), 75 (Crockett et al. 2011), 44 (Dung and Florea 2012), 27 (García et al. 2007), 75 (Graf et al. 2009). It is also important to stress that most approaches were tested with computer science students. It should be noted that only one study was conducted with elementary school students and three with high school students. This implies that further research has to be done with bigger populations on varied contexts, as learning style preferences are influenced by previous knowledge and the environment.

Another issue is how to evaluate and compare the presented results since many differences exist regarding population size, discretization of learning style dimensions and reported metrics. For instance, Felder (Felder and Spurlin 2005) proposes to discretize learning preferences in 3 intervals: strong preference for a learning style on one pole of the dimension, mild preference, and strong preference for a learning style on the other pole of the dimension. However, in the works of Cha et al. (2006b) and Crockett et al. (2011) the mild preference was ignored and only the two extremes of each dimension were considered. Ignoring students with mild preferences simplifies the automatic detection of learning styles, since this type of students are difficult to detect because they frequently switch preferences between both extremes of the learning style dimension. Although ignoring mild preferences simplifies the detection, it should be noted that many students are not taken into account, since the percentage of students with mild preferences can vary from 30 % to almost 70 % (Felder and Spurlin 2005).

Another issue is related to the computation of the precision of the automatic detection approach. Some works, such as García et al. (2007, 2008) and Graf et al. (2008, 2009), apply a formula proposed in García et al. (2007), where the precision is computed by summing up the values returned by a similarity function, divided by the number of samples. The similarity function returns a value of 1 when the learning style detected and the one identified by the instrument are equal. Also, the function returns a value of 0.5 if one of the learning styles represents a mild preference and the other represents a strong preference. Thus, this formula tends to increase the computed precision given that it sums misclassifications between mild and strong preferences, and so it cannot be compared with works that compute the precision without using this formula.

Table 1 Summary of works analyzed

Authors	LS model and instrument	LS model dimensions	LS detection technique	User model information	Number of variables	Educational system	User type	Results	Research type
Ahmad and Shamsuddin (2010)	Felder (ILS)	Processing	Bayesian networks (BN)	User behavior	20	–	Simulated data	BN: 82 %	Experimental
		Perception						DT: 94 %	
		Input	Decision trees (DT) Rules					Rules: 81 %	
		Understanding							
Alkhuraiji et al. (2011)	Felder (ILS)	Processing	Bayesian networks	User performance	Number of responses	–	–	A new approach for content adaptation	Theoretical
		Perception							
		Input							
		Understanding							
Bousbia et al. (2010)	Felder (ILS)	Processing	Correlation analysis	User behavior	4	LMS	CS university students	Perception correlated with navigational behaviors	Experimental
		Perception							
		Input							
		Understanding							
Carmona et al. (2008)	Felder (ILS)	Processing	Dynamic Bayesian networks	User feedback	6	–	–	A new approach for modeling students' learning styles	Theoretical
		Perception							
		Input							
		Understanding							

Table 1 continued

Authors	LS model and instrument	LS model dimensions	LS detection technique	User model information	Number of variables	Educational system	User type	Results	Research type
Carver Jr et al. (1999)	Felder (–)	Perception	Literature-based	User behavior	9	AEHS (CS383)	Students	Improved students' knowledge	Experimental
		Input							
		Understanding							
Cha et al. (2006a)	Felder (ILS)	Processing (Pr)	Decision trees (DT)	User behavior	58	AEHS (CREDITS)	–	For DT:	Experimental
		Perception (Pe)						Pr: 77 %	
		Input (In)						Pe: 88 %	
		Understanding (Un)						In: 100 %	
								Un: 71 %	
Cha et al. (2006b)			Hidden Markov model (HMM)					For HMM:	
								Pr: 77 %	
								Pe: 88 %	
								In: 86 %	
								Un: 86 %	
Chang et al. (2009)	Custom (Custom)	Dilatory	K-NN Genetic algorithms	User behavior	8	LMS	Elementary students	Accuracy of 87 %	Experimental
		Transitory							
		Persistent							
Crockett et al. (2011)	Felder (ILS)	Perception	Fuzzy decision trees	User behavior (conversation interaction)	41	ITS (OSCAR)	CS university students	Pe: 86 %	Experimental
		Understanding						Un: 88 %	

Table 1 continued

Authors	LS model and instrument	LS model dimensions	LS detection technique	User model information	Number of variables	Educational system	User type	Results	Research type
Dung and Florea (2012)	Felder (ILS)	Processing	Literature-based	User behavior	2	AEHS (POLCA)	CS university students	Pr: 72 %	Experimental
		Perception						Pe: 70 %	
		Input						In: 80 %	
		Understanding						Un: 66 %	
García et al. (2007)	Felder (ILS)	Processing	Bayesian networks	User behavior	14	LMS (SAVER)	CS university students	Pr: 66 %	Experimental
García et al. (2008)		Perception						Pe: 80 %	
		Understanding						Un: 72 %	
Georgiou and Makry (2004)	Kolb (–)	Accommodating	Fuzzy-neural networks	–	11	–	–	A new approach for modeling students' learning styles	Theoretical
		Diverging							
		Converging							
		Assimilating							
Gilbert and Han (1999)	Custom (–)	Auditory	Case-based reasoning	User performance	Number of responses	AEHS (Arthur)	–	A new approach for content adaptation	Theoretical
		Visual							
		Tactile							

Table 1 continued

Authors	LS model and instrument	LS model dimensions	LS detection technique	User model information	Number of variables	Educational system	User type	Results	Research type
Graf et al. (2008)	Felder (ILS)	Processing	Literature-based	User behavior	27	AEHS (DeLeS)	CS university students	Pr: 79 %	Experimental
		Perception						Pe: 77 %	
Graf et al. (2009)		Input						In: 77 %	
		Understanding						Un: 73 %	
Kelly and Tangney (2006)	Gardner (MIDAS)	Verbal/Linguistic	Naive Bayes	User behavior	8	AEHS (EDUCE)	High school students	Students learned more in the least preferred condition	Experimental
		Logical/ Mathematical							
		Musical/Rhythmic							
		Visual/Spatial							
Kolekar et al. (2010)	Felder (–)	Processing	Neural networks and web usage mining	User behavior	–	–	–	A new approach for modeling students' learning styles	Theoretical
		Perception							
		Input							
		Understanding							

Table 1 continued

Authors	LS model and instrument	LS model dimensions	LS detection technique	User model information	Number of variables	Educational system	User type	Results	Research type
Latham et al. (2012)	Felder (ILS)	Processing (Act/Ref)	Literature-based	User behavior (conversation interaction)	13	ITS (OSCAR)	CS university students	Act: 100 %	Experimental
								Ref: 73 %	
		Perception (Sen/Int)						Sen: 70 %	
								Int: 80 %	
		Input (Vis/Ver)						Vis: 80 %	
								Ver: 71 %	
		Understanding (Seq/Glo)						Seq: 82 %	
								Glo: 61 %	
Lo and Shu (2005)	Custom (Custom)	Visual	Neural networks	User behavior	7	LMS	CS university students	Accuracy of 90 %	Experimental
		Auditory							
		Kinesthetic							
Özpolat and Akar (2009)	Felder (ILS)	Processing	Decision trees and binary relevance	User behavior (keywords in a web search)	4	Web search engine	CS university students	Pr: 70 %	Experimental
		Perception						Pe: 73 %	
		Input						In: 53 %	
		Understanding						Un: 73 %	
Popescu (2009)	Custom (Custom)	Visual/Verbal (VV)	Literature-based	User behavior	More than 100	AEHS (WELSA)	CS university students	VV: 74 %	Experimental
		Abstract/Concrete (AC)						AC: 82 %	

Table 1 continued

Authors	LS model and instrument	LS model dimensions	LS detection technique	User model information	Number of variables	Educational system	User type	Results	Research type
		Serial/Holistic (SH)						SH: 78 %	
		Active/Reflective (AR)						AR: 85 %	
		Careful/Not careful (CN)						CN: 71 %	
		Individual/Team (IT)						IT: 64 %	
Sanders and Bergasa-Suso (2010)	Felder (ILS)	Processing	Probabilistic models	User behavior	–	AEHS (iLessons)	CS university students	Pr: 81 %	Experimental
		Perception						Pe: 40 %	
		Input						In: 82 %	
		Understanding						Un: 69 %	
Sangineto et al. (2008)	Felder (ILS)	Processing	Literature-based	User behavior	–	AEHS (IWT)	Employees	Improved learning experience	Experimental
		Perception							
		Input							
		Understanding							
Stash et al. (2006)	Custom (ILS)	Active/Reflective	Instructional and monitoring strategies	User behavior	–	AEHS (AHA!)	CS university students	A new approach for providing content adaptivity in a LS model independent way	Experimental
		Verbalizer/Imager							

Table 1 continued

Authors	LS model and instrument	LS model dimensions	LS detection technique	User model information	Number of variables	Educational system	User type	Results	Research type
		Holist/Analytic							
		Field dependent/Field independent							
Stathacopoulou et al. (2005)	Biggs (BILS)	Deep/Surface	Fuzzy-neural networks	User behavior	3	–	Simulated data	Accuracy of 94 %	Experimental
Villaverde et al. (2006)	Felder (–)	Processing	Neural networks	User behavior	10	–	Simulated data	Accuracy of 69 %	Experimental
		Perception							
		Understanding							
Yannibelli et al. (2006)	Felder (–)	Processing	Genetic algorithms	User behavior	9	–	Simulated data	Pr: 80 %	Experimental
		Perception						Pe: 100 %	
		Understanding						Un: 100 %	
Zatarain-Cabada et al. (2009)	Felder (ILS)	Processing	Fuzzy-neural networks	User performance	2	ITS (Zamna)	Teachers and students	A new approach for modeling students' learning styles	Experimental
		Perception							
		Input							
		Understanding							

Table 1 continued

Authors	LS model and instrument	LS model dimensions	LS detection technique	User model information	Number of variables	Educational system	User type	Results	Research type
Zatarain-Cabada et al. (2010a) Zatarain-Cabada et al. (2010b)	Felder (ILS)	Perception Input Understanding	Neural networks and self-organized maps	User performance	4	ITS (Zamna)	High school students	Accuracy of 16 % to classify all three dimensions. Accuracy of 66 % to classify at least two dimensions	Experimental

The automatic detection of learning styles addresses several issues related to questionnaires, namely: students' lack of motivation, arbitrary choice of answers, students influenced by questions, and lack of awareness. As Fig. 6 shows, an approach based on automatic detection of learning styles seems to be an appropriate alternative to questionnaires since, besides addressing the issues previously mentioned, these approaches exhibit an accuracy that ranges from almost 70 % to more than 90 %. However, a questionnaire is a simpler and briefer approach that an educational system can use to provide content adaptation immediately after the questionnaire is answered. In contrast, an approach based on automatic detection requires the student to use the educational system for a while in order to automatically detect learning style preferences and then adapt the learning material. Also, one common characteristic of the approaches used for automatically detecting learning styles is that the user model and automatic detection technique are highly coupled to the educational system. This makes it extremely difficult to reuse the proposed approach in other systems. Thus, a general approach capable of integrating to several educational systems would be very valuable.

8.4 Summary

To sum up, in this work we have described the process of automatic detection of learning styles and analyzed the components that play a role in this process. We have also presented and analyzed several approaches for automatically detecting learning styles based on these components and have outlined some open issues and research gaps that need to be addressed.

In Table 1 we summarize the approaches analyzed in this literature review. In that table, we enumerate the analyzed works (column *Authors*), the learning style model and instrument used (column *LS model and instrument*), the learning style automatic detection technique applied (column *LS detection technique*), the information used to build the user model (column *User model information*), the number of variables the user model has (column *Number of variables*), the system used to detect learning styles (column *Educational system*), the type of users that participated in the experiments (column *User type*), the main results reported (column *Results*) and the type of research done (column *Research type*).

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