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Automatic generation of clinical algorithms within the state-decision-action model

John A. Bohada, David Riaño *, Joan A. López-Vallverdú

Research Group on Artificial Intelligence (BANZAI), Department of Computer Engineering and Mathematics, Universitat Rovira i Virgili, Av. Països Catalans 26, 43007 Tarragona, Spain

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ABSTRACT

Objective: To propose a methodology to automatically induce state-decision-action diagrams from health-care databases and electronic health records in order to show health-care professionals an explicit representation of the past health-care procedures carried out in a health-care organization and to use these representations to study the deviations with respect to official and predefined protocols and clinical algorithms.

Materials and methods: The methodology is based on two data and knowledge structures: *episode of care database* and *set of rules*. These two structures contain, respectively, patient data from health-care centres and the translation rules which are used to adapt the data of the episode of care database to the terminology we want the resulting state-decision-action diagram to have. The data expressed in the new terminology is used to generate the final state-decision-action diagram by means of a machine learning method.

Materials and methods: We have performed several tests on the treatment of hypertension with data from the SAGESSA Health-care Group in Spain. The state-decision-action diagrams obtained have been analyzed at the level of their ability to predict correct treatments and at the level of their adherence to the clinical algorithms published by four official health-care organizations.

Results: The state-decision-action diagrams obtained represent an average 94.6% of the treatments in the database, only excluding some atypical cases. Moreover, these diagrams show a high level of adherence to the treatment proposed by the National Heart Foundation of Australia and the Spanish Society for Hypertension with about 90.4% of coincident treatment.

Conclusions: A new methodology has been developed and validated which automatically induces state-decision-action diagrams which can be used as a graphical representation of the health-care procedures carried out in health-care organizations. The methodology is also a tool to study the adherence of these health-care procedures to the official standards.

1. Introduction

The databases of health-care centres are an unavoidable source of information about the medical procedures followed in these centres. They can be the basis for important studies on the adherence of the treatments to the medical standards that are published as *clinical practice guidelines* (CPGs), and also to foster quality, equality, equity, and cost reduction of medical procedures. This sort of studies for the analysis of health-care procedures can be carried out using either a statistical (Murray, 2004) or a symbolic (Bohada & Riaño, 2004; Riaño, López-Vallverdú, & Tu, 2007) approach. This paper introduces a symbolic approach to the automatic generation of clinical algorithms for the analysis of the health-care procedures followed in health-care centres.

In CPGs, health-care procedures can be represented as *clinical algorithms* (CA) (Hadorn, 1995; Society for Medical Decision Making Committee on Standardization of Clinical Algorithms, 1992). In a previous work (Riaño, 2007; Knowledge Based Homecare eServices for an Ageing Europe – K4CARE (IST-2004-026968), 2006–2009), we introduced the *state-decision-action knowledge model* (SDA) to represent health-care procedures as SDA diagrams which are similar to CAs. Following this work here, we provide a methodology to automatically induce SDA diagrams from health-care databases and electronic health records. The methodology has been implemented and tested on the databases of the SAGESSA Health-care Group (Health Consortium SAGESSA, 2011) for hypertension patients in Spain.

The rest of the paper is organized as follows. In Section 2, we describe the context of our work introducing some background about the representation of procedural knowledge in medicine. Section 3 proposes the methodology to induce procedural knowledge represented as SDA diagrams from health-care databases whose structure fulfils the *episode of care* (EOC) data model (Section 3.1). The

* Corresponding author. Address: Department of Computer Science and Mathematics, Universitat Rovira i Virgili, Av. Països Catalans 26, 43007 Tarragona, Spain. Tel.: +34 977559657; fax: +34 977559710.

E-mail address: david.riano@urv.net (D. Riaño).

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methodology also uses translation rules (Section 3.2) to convert the database into the desired terminology, by means of a pre-processing step (Section 3.3). Once pre-processed, the EOC database is the starting point of a machine learning method which generates the final SDA diagrams (Section 3.4). The results of our work are presented in Section 4. The source data and the pre-processing performed are introduced in Section 4.1. In Section 4.2, the different SDA diagrams obtained are depicted and commented. Then in Section 4.3, an analysis of medical correctness and adherence is described. Finally, a discussion of the work and some conclusions are reported in Sections 5 and 6, respectively.

The paper is complemented with Appendix A that contains a description of the SDA model and a comparison of SDA with traditional CAs.

2. Background

CPGs are used to gather all the available evidence related to a disease. The main arguments justifying the use of CPGs are to provide a homogeneous practice, to improve the quality, the equality and the equity of patient care, and to reduce costs. Some CPGs include CAs (Hadorn 1995; Society, 1992) as a means of summarizing some of the medical procedures that the CPG describe. The CAs introduced by the international (Society for Medical Decision Making, 1992) are flowcharts that start with a *clinical state box* defining the clinical state or problem addressed, and then a combination of both, *decision boxes* representing yes-no questions leading the process to alternative paths, and *action boxes* describing actions, either therapeutic or diagnostic. All these boxes are connected by arrows that show the logical sequence of application of the CA. For example, the CA in Fig. 1 was published by the Institute for Clinical Systems Improvement (Schwartz, 2006) as a generalization of the long term treatment and follow up of hypertension. This CA starts with a state box that identifies the patients with an elevated *blood pressure* (BP) that must be confirmed, as the action box indicates. Then the patient is classified according to whether BP is in stage 1 or 2 (see related table, in Fig. 1) and alternative treatments are provided depending on the suspicion of secondary causes. This differentiation is represented with a decision box: if there is evidence that the BP condition is the result of a secondary cause, an action box orders additional work-up and it recommends considering referral to a specialist. If there is not a secondary cause for high BP, lifestyle modifications and/or drug therapy define the initial treatment. If this treatment is not efficient, then a change of treatment is started. If this change of treatment does not improve BP, then the CA tells us to consider whether hypertension is resistant (i.e., BP goals are not met despite compliance with optimal doses of three antihypertensive drugs of different classes with one of the agents being a diuretic) or not. If BP is not resistant, a second change of treatment is tried; otherwise the patient is referred for consultation.

Note that the level of abstraction of this CA is such that the decision about the concrete drug therapy and the sorts of lifestyle modifications is left to the physician since there is not an agreed configuration of drug treatments but many accepted combinations.

Computer-interpretable guidelines (CIG) are a way of bringing CPGs into practice at the point of care. Some of the most referred systems to represent CIGs are Asbru (Shahar, Miksch, & Johnson, 1998), EON (Tu, 2006), GLIF (Boxwala et al., 2004), and PRO*forma* (Fox, Johns, & Rahmanzadeh, 1998). As we explain in the next lines, the approach of all these systems is to convey knowledge from human experts to machine structures by means of knowledge engineering procedures, and then provide health-care professionals with computer tools to access and exploit that knowledge.

Due to this man-to-machine approach, we may conclude that all the systems to represent CIGs share, among others (Isern & Moreno, 2008; Mulyar, Van der Aalst, & Peleg, 2007; Peleg et al., 2003; Phil et al., 2002), two significant features which are: a great expressiveness of their constructs, and a computer orientation. Expressiveness is required since they have to provide a way to incorporate all the medical variability that may appear in a CPG, which is potentially very high, in the CIG. On the other hand, the computer orientation of such systems is the consequence that they are not designed to be directly applied by health-care professionals but through the use of computer tools, and therefore CIGs are computer structures rather than medical structures.

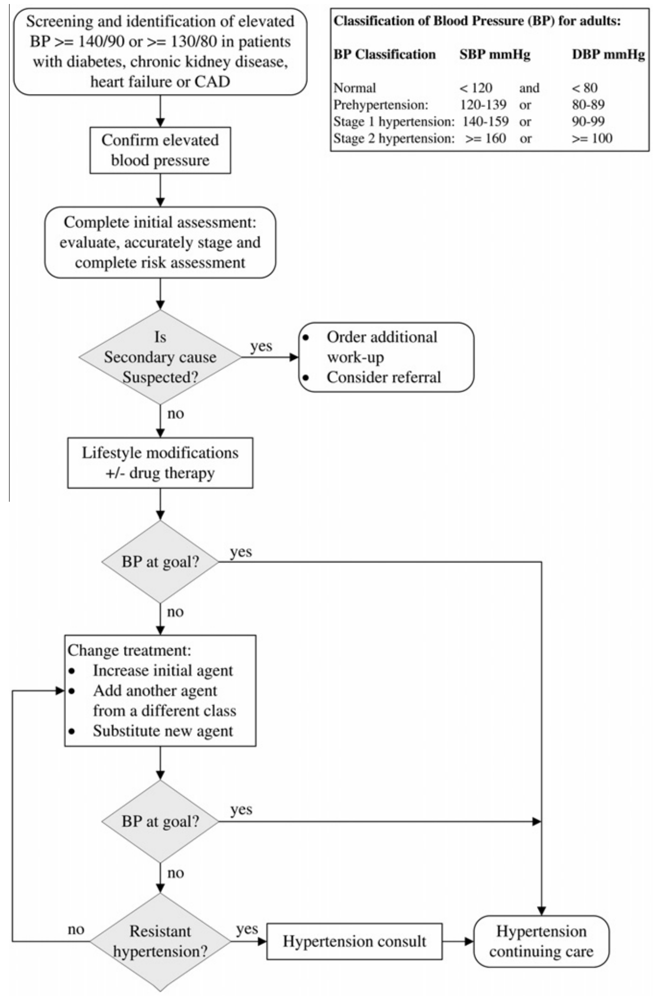

Fig. 1. ICSI clinical algorithm for the treatment of hypertension.

Contrarily, the approach of our work is to convey knowledge in the opposite way, i.e., from computers to health-care professionals. With this machine-to-man approach, the knowledge obtained is not necessarily based on the medical evidence but on the experience of the medical daily practice. Some previous works on this approach include the induction of clinical pathways represented as Petri nets (Mans et al., 2008; Van der Aalst et al., 2003) or as causal Bayesian networks (Mani & Aliferis, 2007). Unfortunately, the structures induced by those systems are not explicit medical structures that doctors are as familiar to work with as with CAs. Moreover, Bayesian networks are not used to represent guidelines in the strict sense of continuous long-term care (Mani & Aliferis, 2007) but punctual decisions in diagnostic and prognostic reasoning, treatment selection, or discovering functional interactions between genes (Lucas, Van der Gaag, & Abu-Hanna, 2004). On the contrary, we propose a process which starts with the data stored either in health-care centre databases or in electronic health records, then these data are analyzed by a machine learning methodology to automatically induce health-care knowledge structures that represent the health-care procedures carried out in the health-care centre in the long-term and in a format that doctors are familiar with. The final purpose of these knowledge structures is to show health-care professionals an explicit representation of the past health-care procedures and to use these representations to study their deviations with respect to official and predefined protocols and CAs.

In our approach, the complexity of the machine learning methodology is directly related to the complexity of the model used to represent procedural knowledge. This dependency forces the sort of knowledge representation system to be not only representative of medical procedures, but also understandable to professionals who are not necessarily trained in formal knowledge representation languages such as Asbru, EON, GLIF or PROforma, and as simple as possible to ease the machine learning process. These requirements recommend us not to use the above mentioned CIG systems. On the contrary, SDA (Riaño, 2007) is a representation model similar to CAs (see Appendix A) that meets all these requirements (i.e., it is representative, understandable to physicians without training, and simple), therefore, SDA is the formalization chosen in this work to represent health-care procedures.

3. Materials and methods

Health-care databases are a source of potential knowledge on the medical procedures followed in health-care institutions. The difficulty of dealing with hundreds or thousands of data can be overcome with the use of intelligent machine learning algorithms that make the knowledge behind these data explicit. We propose a methodology to generate SDA diagrams similar to CAs that generalize health-care procedures from health-care databases. These SDA diagrams are induced by maximizing the adherence to the data while maintaining its capability of generalization. Fig. 2 shows a diagram of the proposed methodology.

The methodology is based on two initial structures, the EOC database and the set of rules, which contain, respectively, patient data from a health-care centre whose structure fulfils a predefined *EOC data model*, and some user-defined *translation rules* which are used in the *pre-processing* step to adapt the data of the EOC database to the terminology the final users want the resulting SDA to have. The data obtained after the pre-processing is used to generate the final SDA diagram by means of a machine *learning* method.

All these elements (i.e., the EOC data model, the translation rules format, the data pre-processing step, and the machine learning method) are described in the next subsections.

3.1. The EOC data model

An *EOC* of a particular patient is the sequence of encounters aiming at curing, stabilizing, or palliating one or several of that patient's ailments (Hornbrook, Hurtado, & Johnson, 1985). Concerning a single *encounter*, the standard behaviour of a health-care professional is to observe the current *state* (and antecedents) of the patient and then decide some *actions*. Observe that some *evidence* may exist that justify these *actions*. Therefore within the same encounter, several *health-care measures* may coexist containing, each one, the evidence to a subset of the actions performed during that encounter. For example, in the hypertension domain, for a particular encounter the physician may decide both a drug therapy based on the evidence that the patient is at high risk of cardiac disease, and a recommendation to modify the patient lifestyle, due to the presence of cholesterol.

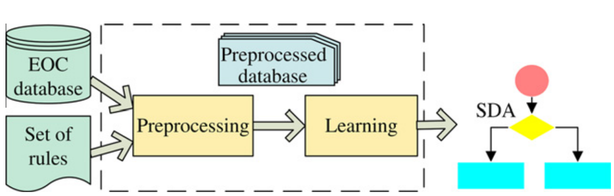

Fig. 2. Scheme of the automatic generation of SDA diagrams.

A simplified formalization of the EOC data model can be seen in Table 1.

An EOC database satisfies the restrictions of the EOC data model in Table 1, and it describes the state and decision data as variable-value pairs (e.g., *SBP* = 140) and distinguishes non-pharmacological action data as the name of the action (e.g., *RECOMMEND_DIET*) and pharmacological action data as expressions of the form: *increase_dose*_D, *decrease_dose*_D, *maintain_dose*_D, *remove*_D, *prescribe*_D and *maintain*_D; where D is the name of a drug (e.g., *increase_dose_AMLODIPINE*).

3.2. Translation rules

In order to convert a health-care centre EOC database to a concrete terminology, we use translation rules. This conversion is not only a means to adapt any EOC database to a common format, but also the way to decide which are the state, decision, and action terms that we want our final SDA be expressed with, and the way each term is calculated from the data contained in each encounter of the EOC database.

A query is used to recover the data contained in each one of the encounters in the EOC database. These data can be of the sort {*var*, *val*} as for example {SBP, 140} meaning that the patient in that encounter had a systolic blood pressure of 140 mmHg; or of the sort {*act*} as for example {*prescribe_DIUREX_20MG*} meaning that during that encounter the patient was prescribed Diurex 20 mg.

The information retrieved from each encounter in the EOC database is transformed into state, decision or action terms depending on whether we want this information to appear in states, decisions or actions of the SDA obtained after the machine learning step. A set of translation rules guides the transformation of the data in the EOC database into the terms to be contained in the SDA. A *translation rule* is an expression of the form $t \leftarrow p$, where t is a SDA term and p is a constraint on the encounter data. If the encounter data fulfils p, the translation rule is triggered generating the output term t. Using a set of translation rules, a new EOC database can be created where the data in each encounter has been replaced by SDA terms.

There are two kinds of translation rules, one for states and decisions and another one for actions. In the first kind, t is either a state or a decision term and the constraint p is expressed as a conjunction of conditions of the form {*var s val*} where *var* is one of the variables that can be retrieved from the database, s is one of the comparison symbols =, <, >, <=, >=, <> or the same symbols preceded by an exclamation mark (!) meaning the negation of the symbol or unknown value; and *val* is either a numerical, multi-valued or Boolean value, or another variable. For example, the translation rule (1) will introduce the decision term "*BP_at_goal*" in all the encounters of the database in which the systolic blood pressure (*SBP*) and the diastolic blood pressure (DBP) of the patient are lower than 140 and 90 mmHg, respectively.

$$BP\_at\_goal \leftarrow \{SBP < 140\} \,\&\, \{DBP < 90\} \tag{1}$$

$$Drug\_Therapy \leftarrow prescribe\_DIUREX\_20\text{ mg} \tag{2}$$

In the second kind of translation rules, t is a SDA action term and the constraint p is expressed as a conjunction of variables from the database. For example, rule (2) will introduce the action term

Table 1
Simplified formal description of the EOC data model.

Episode of care	← EOC-DATE + sequence of encounters	An EOC starts in a date and has a list of encounters
Encounter	← E-DATE + patient condition + set of health-care measures	An encounter has a date, the current health condition of the patient and a set of medical actuations
Patient condition	← set of state data	The health condition of a patient is described by relevant antecedents, signs, symptoms and findings
Health-care measure	← evidence + action	A health-care measure is a medical actuation aimed to treat only one of the health problems of the patient*
Evidence	← set of decision data	Set of data supporting a medical actuation
Action	← set of action data	Set of medical actions within a medical actuation

* During an encounter the physician may treat several health problems simultaneously

"*Drug_Therapy*" in all the database encounters in which the patient is prescribed with Diurex 20 mg.

The set of translation rules must be provided by an expert. The effort providing a set of rules is proportional to the number of terms that we want the SDA diagram to contain and to the number of variables from the database related to these terms.

3.3. Data pre-processing

The pre-processing step in Fig. 2 uses a set of translation rules to adapt the data in an EOC database to the terminology we want the SDA to have. This pre-processing is justified, firstly, by the fact that the database may contain numerical, multi-valued or Boolean values and we want the final SDA to only contain state, decision and action general terms (e.g., the treatment of hypertension must be described in terms of high, normal or low SBP rather than in concrete values of SBP). Secondly, from a medical point of view, it may be of some interest to reflect only part of the treatment or different perspectives of the same treatment, instead of the complete treatment registered in the EOC database. For example, if we are only interested in the nursing activities or in the treatment of critical cases, the data that is not related to nursing or critical treatment should be left out of the learning process. Finally, data pre-processing is useful to integrate data from different health-care centres which may use different terminology. In these cases, pre-processing can be used to make data homogeneous before the machine learning process is started.

Translation rules perform operations on the domain terminology such as generalization, extension, removal and replacement. *Generalization* allows a common term to represent different conditions. Formally, generalization occurs when a unique term t represents several constraints $p1, p2, \ldots, pn$ within the database (i.e., $t \leftarrow pi$ with $i = 1, \ldots, n$). For example if we consider the rules (3) and (4), the action term "*Drug_Therapy*" will generalize the prescription of either Diurex or Dilutol.

$$Drug\_Therapy \leftarrow prescribe\_DIUREX\_20\text{ mg} \quad (3)$$

$$Drug\_Therapy \leftarrow prescribe\_DILUTOL\_10\text{ mg} \quad (4)$$

$$Grade\_I/II\_BP \leftarrow \{SBP >= 140\} \,\&\, \{SBP <= 179\} \,\&\, \{DBP >= 90\} \,\&\, \{DBP <= 109\} \quad (5)$$

$$High\_Risk \leftarrow \{SBP >= 140\} \,\&\, \{SBP <= 179\} \,\&\, \{DBP >= 90\} \,\&\, \{DBP <= 109\} \quad (6)$$

$$Initial\_State \leftarrow \{E\text{-}DATE = EOC\text{-}DATE\} \quad (7)$$

$$Intermediate\_State \leftarrow \{E\text{-}DATE <> EOC\text{-}DATE\} \quad (8)$$

$$LifeStyle\_Modification \leftarrow RECOMMEND\_DIET \quad (9)$$

$$Change\_Treatment \leftarrow increase\_dose\_AMLODIPINE \quad (10)$$

Extension is the operation of increasing the vocabulary with synonyms. Formally, the extension occurs when different terms $t1, t2, \ldots, tn$ represent the same constraint p of the database (i.e., $ti \leftarrow p$ with $i = 1, \ldots, n$). For example, the constraints on systolic blood pressure (*SBP*) and diastolic blood pressure (*DBP*) of the rules (5) and (6) give rise to the decision term "*Grade_I/II_BP*" related to the blood pressure level of the patient, and the synonym "*High_Risk*" related to the cardiovascular disease risk.

Removal consists in discarding some data from the database because they are not of our interest. For example, if none of the rules contain the variable *BILIRUBIN* then the final data will not take into account this information about the treatment.

Finally, *replacement* consists in substituting a health condition by an equivalent term. Formally, replacement is the operation of using the term t to refer to a constraint p in the database (i.e., $t \leftarrow p$). For example, the state term "*Initial_State*" is used in our tests to describe the encounters whose date is equal to the date in which the EOC started; this replacement is caused by rule (7).

3.4. The machine learning method

Provided the pre-processed data structured according to the previously described EOC data model, it is possible to generate a SDA diagram, as the one in Fig. 3, that generalizes the individual treatments as a global treatment. The proposed method is depicted in Fig. 4 and it involves five tasks: detect states, detect actions, determine evolutions, determine actions, and integrate.

3.4.1. Task 1: Detecting States

After pre-processing the database with the translation rules, the resulting data is used by an inductive learning method to generate a SDA diagram that generalizes all the individual treatments. The states in a SDA diagram (see circles in Fig. 3) represent the sorts of clinical situations the SDA is designed to manage (see Appendix A for more details). In order to detect all the states that will be part of a SDA, we apply an automatic method which is based on a function of similarity between states. Being $S_1 = \{s_{11}, s_{12}, \ldots, s_{1m}\}$ and $S_2 = \{s_{21}, s_{22}, \ldots, s_{2n}\}$ the respective set of state terms of two encounters of the database, each one representing a state, then a similarity function between these states is defined as the quotient $|S_1 \cap S_2| / |S_1 \cup S_2|$. If it is greater than a predefined threshold $0 \leqslant \alpha \leqslant 1$, these two states are considered to be the same. The threshold chosen depends on the level of detail needed for the SDA diagram. With $\alpha = 0$ there will be only one state in the final diagram, and with $\alpha = 1$ there will be as many states as encounters with a different state are in the data. Alternatively to the automatic detection of states, the user may define the SDA states wished and the state terms that compose each one of these states. For example, the states $S_1 = \{Initial\_State\}$ and $S_2 = \{Intermediate\_State\}$ in Fig. 3.

3.4.2. Task 2: detecting sorts of actions

Clinical actions appear as rectangles in SDA diagrams as Fig. 3 shows. In order to detect all the sorts of actions that will appear in

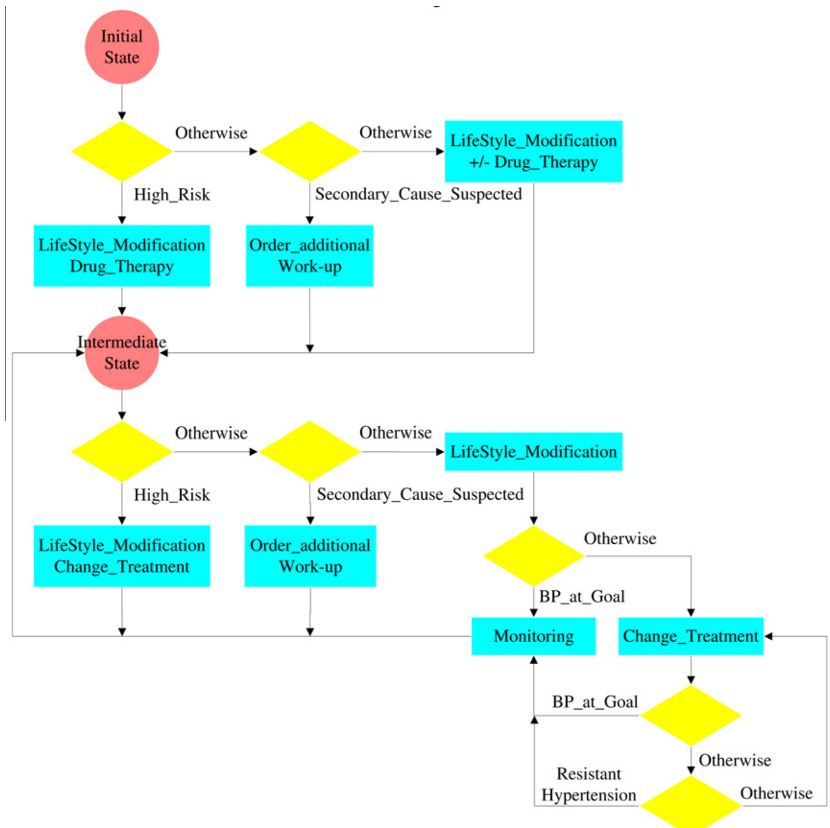

Fig. 3. SDA for the treatment of hypertension.

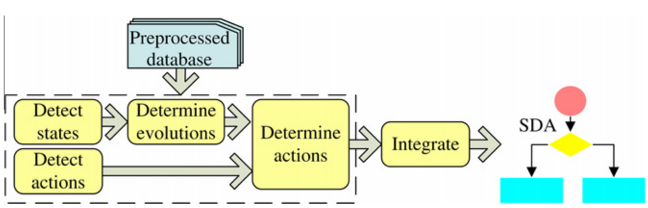

Fig. 4. Generation of SDA diagrams.

the final SDA, an automatic method which is similar to the one described to *detect states* is applied. It is based on a function of similarity between actions. Let $A_1 = \{a_{11}, a_{12}, \ldots, a_{1m}\}$ and $A_2 = \{a_{21}, a_{22}, \ldots, a_{2n}\}$ be the respective sets of action terms of two encounters, then a similarity function between A_1 and A_2 is defined as the quotient $|A_1 \cap A_2| / |A_1 \cup A_2|$. If it is greater than a predefined threshold $0 \leqslant \beta \leqslant 1$, these two sorts of actions are considered to be the same. The threshold chosen depends on the level of detail needed in the SDA diagram. With $\beta = 0$ there will be only one sort of action in the final SDA diagram (i.e., the same exact treatment is applied to all the admitted patients), and with $\beta = 1$ there will be as many sorts of actions as encounters with a different action are found in the data (i.e., any difference, small or big, is interpreted as a different treatment). Alternatively, the user may avoid the application of this process and define the available sort of actions by choosing the action terms that compose each one of the wished actions. For example, A_1 = {*LifeStyle_Modification*, *Drug_Therapy*}, A_2 = {*LifeStyle_Modification*, *Change_Treatment*}, etc. in Fig. 3.

3.4.3. Task 3: Separating patients who evolved differently from the same state

Patients that are under the same clinical state may require different treatments depending on their particular health conditions. Determining a correct treatment is the result of making some decisions that are represented as diamonds in the SDA diagram (see Fig. 3). Once the states and the sorts of actions of the final SDA have been determined, the sequences of decisions that drove the physician to prescribe the different treatments in the EOC database have to be found.

For each patient, the sequence of encounters in the EOC database defines a treatment. Each encounter of this sequence describes the patient in one or several of the states obtained in task 1. A patient is considered to be in a state if all the state terms of that state are observed in the patient condition. Task 3 obtains decision sequences that explain how to separate patients in a state that evolve to different states in the next encounter or that are discharging states. This is done by separating, for all the states S_i after task 1, the set of encounters E_i of the patients in that state. For each pair of states S_i S_j (S_j possibly being a discharge state), this process finds a sequence of decisions to partition E_i with a procedure that is inspired in the split criterion used by the C4.5 algorithm (Quinlan, 1993) for decision tree induction. This procedure is the following:

1. Let D be the set of decision terms that appear in some of the encounters in E_i. For each possible subset of decision terms D' in D, a decision is created with as many decisional connectors[1] as decision terms are in D', plus an otherwise connector. Each one of the decisional connectors is assigned a different decision term in D'.

[1] In SDA diagrams, arrows are called connectors. We distinguish between connectors that any patient can follow (*plain connectors*), connectors labeled with decision terms that only patients satisfying these terms can follow (*decisional connectors*) and connectors leaving decisions that only patients satisfying none of the other connectors leaving that decision can follow (*otherwise connectors*).

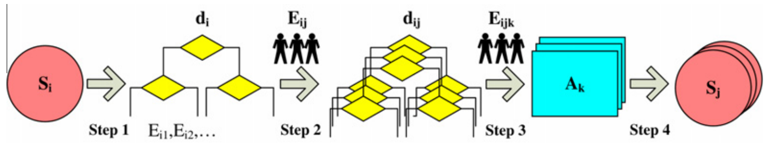

Fig. 5. Integration of states, decisions and actions in the SDA.

2. Among all the decisions obtained, the best one is the decision that provides a higher information gain (Maktelow, 1999; Quinlan, 1993) to predict the state of the next encounter.
3. For each connector of the best decision, we separate the encounters in E_i that contain the decision term in this connector. The encounters containing none of the decision terms in the connectors are separated in an additional subset corresponding to the otherwise connector.
4. For each one of these subsets of encounters E_i‘, the corresponding connector is linked to the decision that is obtained after applying this same procedure to E_i‘. The process is repeated until all the encounters in each subset correspond to patients that evolved from an initial state S_i to one same state S_j. At the end, we obtain d_i, a tree-like combination of decisions which partitions E_i (encounters of patients in state S_i) into several subsets of encounters E_{ij} (encounters of patients who evolved from S_i to S_j). This process is represented as the first step in Fig. 5.

3.4.4. Task 4: determining the correct action for the patients of each evolution

Once the patients who evolved from the same state S_i to a next state S_j have been separated from those who evolved to a state different from S_j, each one of the combinations of decisions d_i is extended with other combinations of decisions that decide which is the action that defines the treatment of the patients following this evolution. The same process described for task 3 is applied to all the subsets of encounters E_{ij} but, in this case, the selection of the best decision is based on the information gain to predict the sort of action performed rather than the expected next state. The process is repeated until all the encounters in a subset correspond to patients that are treated with the same sort of action. We call d_{ij} the tree-like combination of decisions which partitions E_{ij} into several subsets E_{ijk} (encounters of patients who evolved from S_i to S_j receiving the treatment A_k). This is represented as the second step in Fig. 5.

During this partition process, if some encounters in the same subset have the same decision terms but different actions, then we place several decisional connectors with the same decision terms, leading to different actions. In these cases, the following pruning process is incorporated to reduce non-determinism. Given a threshold *p*%, whenever a subset of encounters has less than *p*% of encounters with a same action, these encounters are removed from the subset before any decision is generated. If none of the actions appears in more than *p*% of the encounters, then only the most frequent action is considered.

3.4.5. Task 5: integration

The SDA diagram is obtained as an integration of the states, the sorts of actions and the tree-like combinations of decisions obtained in the previous tasks, as Fig. 5 shows. The states detected in task 1 are the states in the final SDA. The root decision of each d_i is connected after the corresponding state S_i. The root decision of each d_{ij} is connected after the last decisional connector of d_i that leads to E_{ij}. Then, an action is placed after the last decisional connector of each d_{ij} that leads to E_{ijk}. This action is A_k, the one that is performed in all the encounters in E_{ijk}. Each terminal action A_k after d_{ij} is connected to the state S_j. Finally, since the same sort of action can appear several times in the SDA, all the identical actions that lead to the same next state are unified into one single action in order to simplify the final SDA.

4. Results

This methodology to generate SDAs from EOC databases has been tested using the patients treated of hypertension in the SAGESSA Health-care Group (Health Consortium SAGESSA, 2011) and the resulting SDAs analyzed from three points of view: their medical validity, their ability to predict correct treatments and their similarity to already existing official CAs.

4.1. Source data and pre-processing

The methodology has been tested on the medical domain of hypertension, which is one of the most common chronic diseases. The EOC database was provided by SAGESSA (Health Consortium SAGESSA, 2011). The database contained 1092 encounters corresponding to the follow-up of 10 different chronic patients during 8 years that evolved through all different stages of the disease (i.e., prehypertension, stage 1 and stage 2).

With the purpose of studying the differences between the health-care procedures of the EOC database and some predefined official CAs, a set of translation rules was developed for each one of the four CAs on hypertension provided by ICSI (Schwartz, 2006), SIGN (MacWalter R., 2001), NHF (National Heart Foundation of Australia, 2008), and SEH (Sociedad Española de Hipertensión, 2005). This process was carried out in cooperation with a group of physicians leaded by Dr. Collado, a senior GP of SAGESSA with more than 30 years of experience in the treatment of hypertension, who confirmed the medical validity of the final rules. The above mentioned CAs were represented as the SDA diagrams that are provided in Fig. 6 and validated by these physicians. Then, each set of translation rules was used to convert the data in the SAGESSA database to the terminology of each one of the respective CAs before the machine learning methodology was applied. After this process, the induced SDA diagrams and the CAs in Fig. 6 were respectively expressed in the same medical terms and, therefore, the clinical procedures that they represent able to be pairwise compared. A total number of 379 sorts of operations were performed with the translation rules. These rules did not contain additional medical knowledge but only the matching between the data in the SAGESSA database and the terminology used by the different official CAs. They are not provided in this work because they are of low interest in the learning process introduced here and also because of their extension.

However, the number of each sort of operation performed with the translation rules are summarized in Table 2. This table informs about the number of state, decision and action terms required in ICSI, SIGN, NHF and SEH, and also about the number of terms that have been generalized and the number of generalization rules applied. It also shows the number of sorts of extension, removal and replacement operations used in the translation process. The total number of sorts of operations appears in column *Total*.

Removal was the most frequent operation because there were several variables from the database that represented information

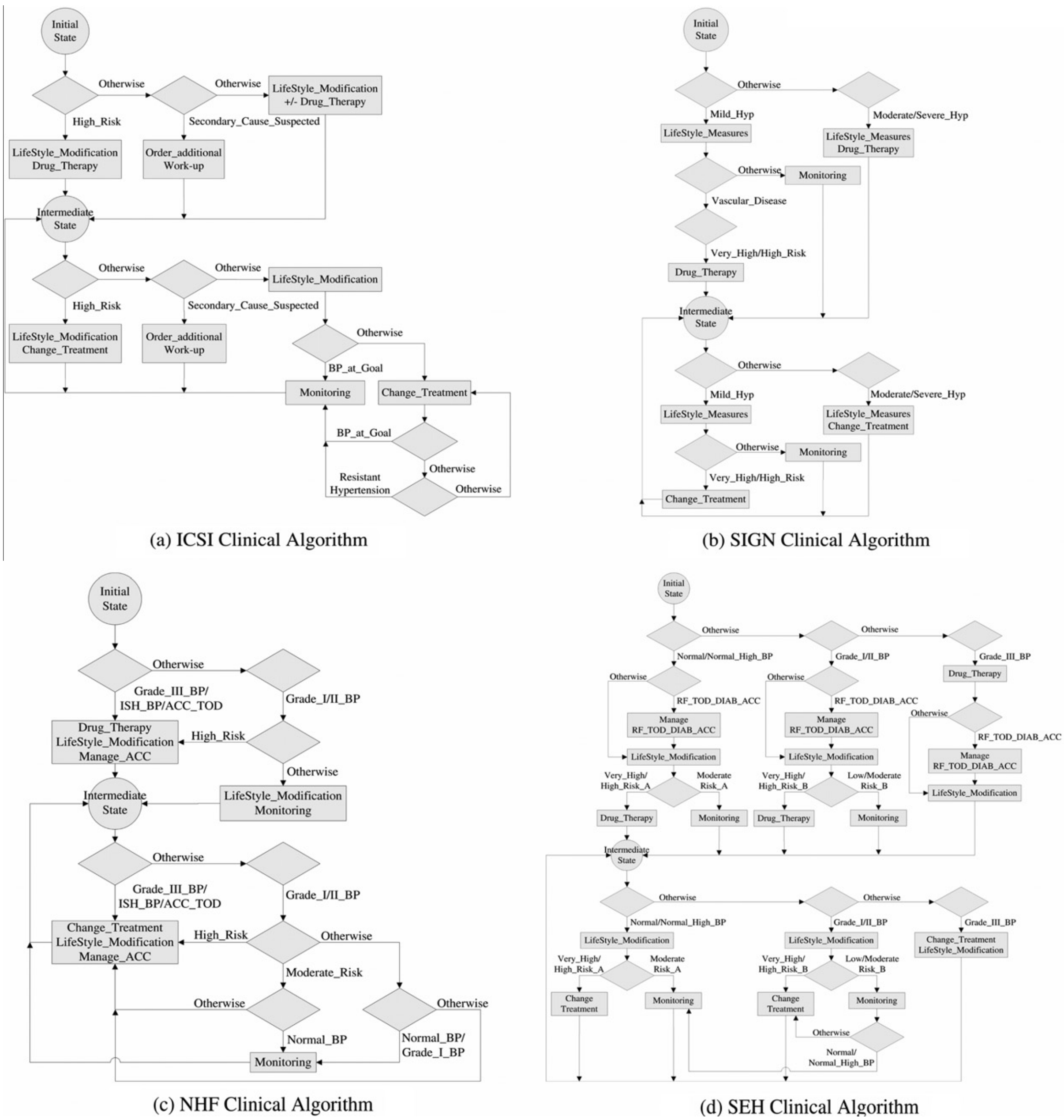

Fig. 6. SDA diagrams obtained from the official predefined CAs for the treatment of hypertension.

Table 2
Number of terms and sorts of operations for pre-processing the EOC database.

	State terms	Decision terms	Action terms	Generalization No of terms/rules	Extension	Removal	Replacement	Total
ICSI	2	4	5	8/75	0	75	3	86
SIGN	2	4	4	7/94	0	91	3	101
NHF	2	6	5	10/94	0	80	4	94
SEH	2	8	5	15/161	0	80	3	98

that was not present in the official CAs (e.g., *BILIRUBIN*). All the terms in the official CAs could be directly extracted from the EOC database; therefore, operations of the sort *extension* were not necessary. Operations of the sort *generalization* and *replacement* were used in all four cases (e.g., *LOW_SALT_DIET* was replaced by the term "*LifeStyle_Modification*" and "*LifeStyle_Measures*" in ICSI and SIGN, respectively). The main differences are found in the number of *generalizations*, this is so because the number of decision terms in NHF and SEH is higher than in ICSI and SIGN, and more operations were needed to generate these additional terms.

4.2. The medical validity of the obtained SDA diagrams

Fig. 7. depicts the SDA diagrams that were obtained from the EOC database after pre-processing the data with the respective sets of translation rules. During the learning process several physicians

of SAGESSA recommended us to fix $\alpha = 1$ and $\beta = 1$ in order to obtain the most detailed SDA diagrams possible on which these physicians performed a validation process. In this process they were asked to assess several issues of the SDA diagrams induced: flexibility (i.e., capacity of the SDA diagrams to capture the treatment alternatives), generality (i.e., ability of the diagrams to deal with the variability of patient cases), medical appropriateness (i.e., medical and clinical correctness), common behaviour (i.e., capacity of the diagrams to capture usual treatments), level of detail (i.e., the treatments in the diagrams have the appropriate degree of abstraction), and comprehension (i.e., the diagrams are clear and easy to understand).

The physicians evaluated satisfactorily all these issues and they remarked an outstanding performance with regard to flexibility, medical appropriateness, level of detail, and comprehension. So, for example, they argued that all the diagrams describe treatments that are more flexible than the corresponding official CAs depicted in Fig. 6 because they include non-determinism in some of the decisions and this allowed alternative correct therapies. For example in Fig. 7(a), the decision on the left side has three decisional connectors with the decision term "*High_Risk*" leading to different actions. This reflects that some physicians of SAGESSA whose treatments were registered in the EOC database did not always act according to the exact indications in the CAs, but providing alternative treatments under the same patient circumstances.

This behavior was qualified as appropriate and common by independent physicians.

Medical doctors also argued that the level of detail of pharmacological treatment in the diagrams was adequate to the treatment of hypertension where many correct drug combinations are possible for the same medical case. Introducing such level of detail in the SDA diagrams increased their complexity after incorporating many different alternative valid treatments.

During the analysis of the results, physicians appreciated some structural differences between the standard CAs in Fig. 6 and the obtained SDAs in Fig. 7. Also according to the treatments provided in SAGESSA, the procedures carried out in the first encounter are more general than those proposed by the CAs. For example, SEH uses BP, the associated clinical conditions (RF_TOD_DIAB_ACC)[2] and the risk levels (of types A and B)[3] for making decisions in the first encounter (see Fig. 6(d)) whereas the procedures followed in SAGESSA do only consider BP in the first encounter (see Fig. 7(d)), and leave the rest of conditions for later consideration. Another difference that physicians liked because it brings additional information is that SDAs include a third new state to represent patient discharge, which is depicted in Fig. 7 as unlabeled states.

This validation of the SDAs done by several physicians in the SAGESSA group was complemented with two additional analyses: medical correctness and adherence.

4.3. Analysis of medical correctness and adherence

The SDAs in Fig. 7 have been analyzed both to verify that the learning method introduced in Section 3.4 is correct from a medical point of view (i.e., the induced SDA captures the correct medical procedures hidden in the data) and also to check the adherence of the obtained SDAs with respect to several predefined standard CAs (i.e., the therapy described by the induced SDAs is similar to the one described by official CAs).

Both correctness and adherence have been calculated in terms of type I and type II errors (Doan, 2005). Type I error is related to the medical relevance of taking a wrong medical decision (e.g., ordering a visit to a specialist when it is not necessary), and type II error is related to the medical relevance of not taking the correct medical decision (e.g., forgetting a drug prescription when it is completely necessary). To calculate these errors in the analysis of the correctness, we registered the deviations between the treatment performed in each encounter of the EOC database and the treatment proposed by the induced SDA. On the other side, in the analysis of the adherence, all the possible patient conditions in the database were considered. These conditions represent all the sorts of registered states a patient can arrive to an encounter. For each patient condition, we considered the probability of having an encounter with a patient with this health condition (i.e., epidemiological information provided by the physicians in SAGESSA). Then, we registered the deviations between the treatment suggested by the CA and the treatment proposed by the SDA as it is described in Section 4.3.2.

In both analyses, each possible deviation of the treatment was given a certain medical relevance provided by the team of health-care professionals. The addition of type I and type II errors is called the total error.

4.3.1. Analysis of the medical correctness respect to real treatments

This analysis was performed to verify the correctness of the methodology in the context of the treatment of hypertension in SAGESSA, that is to say, the level of adjustment of the SDA diagrams to the health-care procedures within the SAGESSA database. In Table 3, the columns *correctness* contain the mean of type I, type II and total errors when the health-care procedures in the EOC database were compared with those proposed by the SDA diagrams in Fig. 7. The pruning in tasks 3 and 4 of the learning process is the main reason for type I and type II errors. An average 0.3% of medical orders suggested by the SDA does not coincide with the database (type I error) and, an average 5.1% of the medical orders in the EOC database are not reflected in the SDAs (type II error).

Table 3 shows that the average correctness of the algorithm in the tests performed is near 95%. As the physicians stated, the results obtained provide evidence on the correctness of the machine learning methodology. After studying the differences between the generated SDA diagrams and the database, the physicians confirmed that this 5.4% of average total error mainly corresponds to atypical actuations but also to some identified errors in the data describing the actuations.

4.3.2. Analysis of the adherence to standards

Medical adherence is defined as the extent to which real medical practices follow the suggestions of medical standards. This serves as a way to determine which type of health-care assistance is rendered in a certain clinical centre. In our case, this analysis was used to determine the adherence of the SDAs of the health-care procedures carried out in SAGESSA to several standard CAs. In Table 3, the columns *adherence* contain the mean of type I, type II and total errors when the health-care procedures proposed by the SDA diagrams in Fig. 7 were compared with those of the CAs (taken as gold-standards). The SDA diagrams have an average type I error of 1.5% and an average type II error of 11.5% with respect to the CAs. The medical interpretation is that the patients of SAGESSA were approximately ten times more under-prescribed than over-prescribed,[4] respect to official CAs. One of the reasons for this differ-

[2] RF: risk factor, TOD: target organ damage, DIAB: diabetes mellitus, ACC: associated clinical conditions.

[3] Risk levels according to SEH.

[4] A patient is over-prescribed when the treatment followed contains actions that are not explicitly recommended in the official treatment (i.e., a positive type I error). A patient is said to be under-prescribed when the received treatment lacks of some actions with respect to the official treatment (i.e., a positive type II error). The under- and over-prescription values in Table 3 represent qualitative rather than quantitative measures of the medical errors.

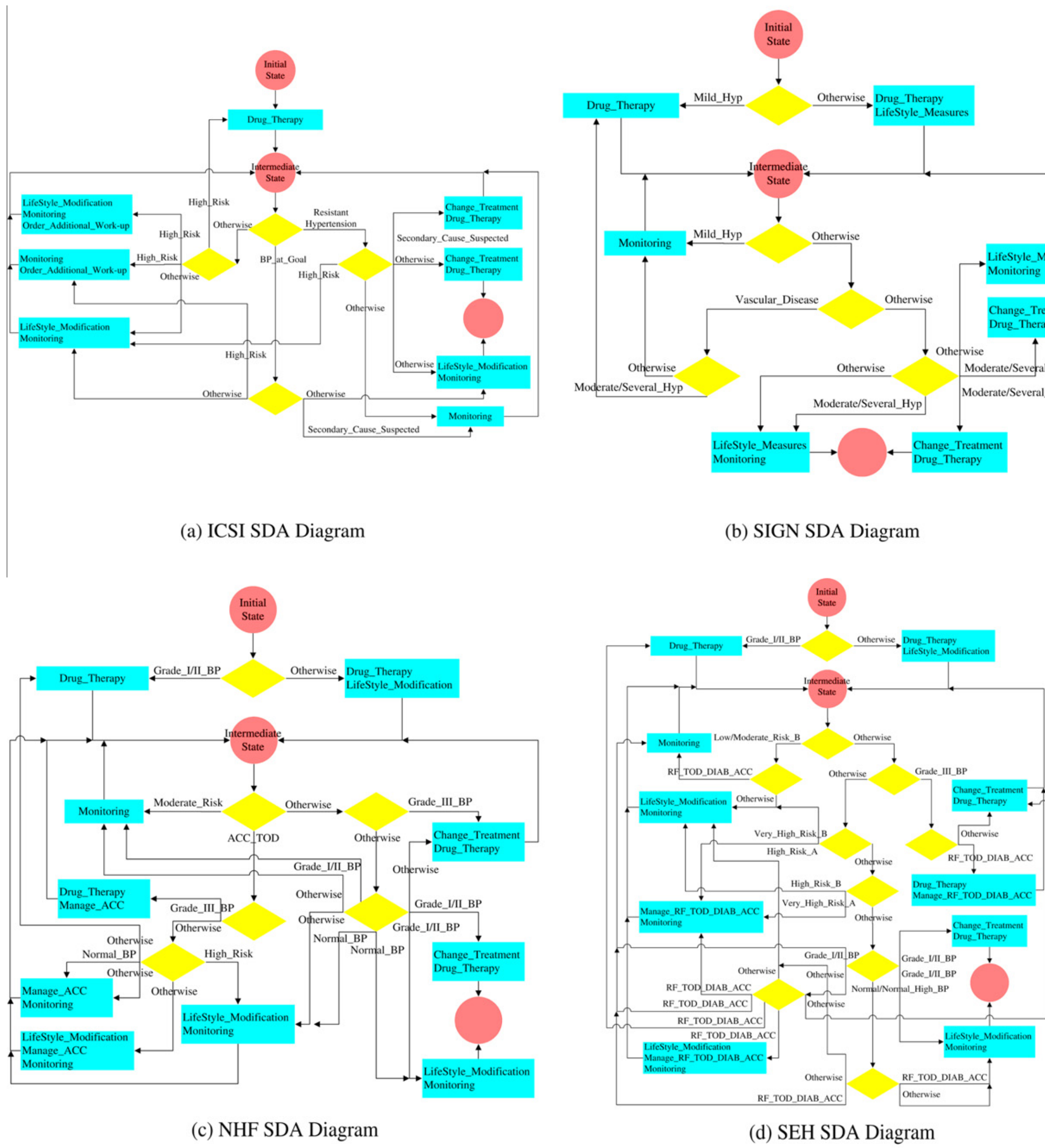

Fig. 7. SDA diagrams induced from the EOC database for the treatment of hypertension.

ence is that in this work and for hypertension, physicians determined that forgetting a medical action is more critical than performing it when it is unnecessary. For example, the medical error of not doing a necessary monitoring of the patient can imply important health consequences. On the contrary, planning an unnecessary monitoring can be a common practice to corroborate the state of the patient, but with null health implications. Therefore, from a medical point of view and in the case of hypertension, type II error was expected to be greater than type I error as the results confirmed.

Observe also that the health-care procedures in the EOC database have a lower total error with respect to the CAs provided by NHF and SEH, than to the CAs provided by ICSI and SIGN. This indicates that the treatment of hypertension in SAGESSA is closer to NHF and SEH indications than to the ICSI or SIGN CAs.

The interpretation of the SAGESSA physicians to these results is related to the fact that health-care in Spain is mainly a public service coordinated by the Spanish National Health Ministry. This Ministry watches for the national health-care centres to provide a homogeneous assistance in all the Spanish regions and it works together with national health societies, as the SEH, to disseminate health-care guidelines. Therefore, it is not surprising that the physicians in a Spanish health-care centre as SAGESSA treat hypertension as it is recommended by the SEH. On the other hand, the good adherence of SAGESSA treatments to the CA of the Australian NHF was unexpected but it also confirmed the similarities between NHF and SEH CAs (see Fig. 6).

Some of the deviations observed in this comparative analysis between official CAs and real treatments have been interpreted and justified by health-care professionals as experience-based knowledge which complements official CAs. For example, the CA of SEH (Fig. 6d) proposes “LifeStyle_Modification” for patients with “Normal/Normal_High_BP”, while the respective induced SDA

Table 3
Average type I, type II and total errors obtained in the SDA-data and SDA-CA analysis of the adherence on hypertension.

Errors	Correctness			Adherence		
	Type I	Type II	Total	Type I	Type II	Total
ICSI	0.004	0.070	0.074	0.016	0.160	0.176
SIGN	0.002	0.083	0.085	0.011	0.139	0.150
NHF	0.003	0.024	0.027	0.018	0.078	0.096
SEH	0.003	0.027	0.030	0.014	0.083	0.097
Average	0.003	0.051	0.054	0.015	0.115	0.130

(Fig. 7d) recommends "Monitoring" in addition to "LifeStyle_Modification". Physicians argue that monitoring is highly recommended also for mild hypertension cases for preventive reasons.

5. Discussion

As far as the authors are aware there are not machine-to-man methods available for inducing procedural knowledge from health-care databases and electronic health records using explicit medical structures that doctors are familiar to work with. Nowadays this kind of knowledge is represented with CIGs as a result of a knowledge engineering process.

Other approaches as the automatic construction of Petri nets (Mans et al., 2008; Van der Aalst et al., 2003) or causal Bayesian networks (Mani & Aliferis, 2007) from health-care data produce knowledge structures that are not as familiar to health-care professionals as CAs and, for Bayesian networks, they do not represent long-term treatments (Mani & Aliferis, 2007) but punctual decisions in diagnostic, prognostic or treatment procedures, or gene analysis (Lucas et al., 2004). Therefore the methodology introduced here is innovative in the sense that it automates the induction of knowledge structures representing the long-term health-care procedures carried out in a health-care centre in a manner that physicians may understand. Moreover, the fact that this knowledge is represented using the SDA model offers several advantages with respect to the classical CA representation as, for example, the representation of long term procedures, the identification of multiple entry points and the possibility of using multi-term decisions and non-determinism.

All the tests presented in Section 4 correspond to hypertension because the following reasons: SAGESSA was interested in the analysis of their databases for this particular disease; hypertension is a controlled well-known medical domain that affects a big percentage of chronic population; it is a common disease of any health-care centre and, therefore, the amount of data available in different centres is (1) representative of the different sorts of treatments, (2) usually non-biased, and (3) sufficient to apply the inductive learning methodology introduced in this work.

Moreover, contrarily to other already analyzed diseases as Chronic Obstructive Pulmonary Disease and certain cancers (Riaño et al., 2007), hypertension is a medical domain with multiple available official CAs and whose treatments are always described at a level of abstraction that avoids the extreme personalization of medical procedures (e.g., considering drug treatment instead of concrete drugs). Both, having several official CAs and being adjusted to the level of abstraction of the terms in these CAs were compelling conditions satisfied by hypertension but not by other diseases considered.

The results obtained provide evidence on the correctness of the machine learning methodology with an average total error of 5.4% when the generated SDA diagrams are compared with the health-care procedures in the source database. According to physicians, this percentage mainly corresponds to atypical actuations but also to some identified errors in the data describing the actuations.

Observe that 94% of this error concerns to type II error (i.e., rejecting decisions which appear in the database of the health-care centre) and 6% to type I error (i.e., proposing additional decisions which do not appear in the database of the health-care centre). So, the learning methodology shows a conservative behaviour with respect to the treatments observed in the database. Furthermore, the methodology has been used to study the differences between the health-care procedures registered in the health-care database of SAGESSA and four official and predefined standards (Schwartz, 2006) (Española de Hipertensión (SEH), 2005; Heart Foundation of Australia (NHF), 2008; MacWalter, 2001). These differences represent an average total error of 13% which is below 10% for NHF and SEH. For hypertension, this means that physicians in SAGESSA are following more than 90% of the recommendations in the clinical algorithms of some official organizations.

The methodology reported in this article has some limitations. The SDA model permits two sorts of time constraints in the diagrams (Kamišalić, Riaño, Real, & Welzer, 2007; Kamišalić, Riaño, & Welzer, 2008): micro and macro-temporality. Micro-temporality is used to attach time restrictions to the terms in the SDA diagram (e.g., durations, frequencies, deadlines, etc.), while macro-temporality is used to attach time restrictions to the connectors in the SDA diagram (e.g., delays, waits, schedules, etc). Here we have not considered the features of time of the SDA model that have been left out for a next future work.

Another limitation is the lack of medical background knowledge in the learning method which may be particularly useful to detect states and actions. Here, the similarity between states (and actions) is done manually or using an approach which is based on the coincidence of terms. In spite of the good results in the study of hypertension, this approach is mathematical rather than medical, which could affect the medical quality of the SDAs obtained for other diseases. In the future, the authors aim to incorporate background knowledge represented by means of ontologies in the machine learning method (López-Vallverdú, Riaño, & Collado, 2012).

Finally, the analysis of the behaviour of the learning method for different abstraction levels of the terminology of the SDA diagram is also left for future work.

6. Conclusion

We proposed a new methodology to machine learn SDA diagrams from the databases of health-care centres. These structures represent procedural knowledge on the health-care activities of such centres. A data model which is based on the concept of EOC is introduced as a means to provide a common design for the health-care databases to induce SDAs. A formalism to represent translation rules is also provided. This sort of rules is used to adapt and translate the data in the databases to the terminology that we want the final SDA diagrams to have.

This machine learning methodology can be used for two purposes. On the one hand, to generate SDA diagrams that serve as graphical representations of the health-care procedures carried out in health-care centres. We have tested it over the database of the SAGESSA Health-care Group obtaining a SDA diagram which represents an average 94.6% of the treatments in the database, only excluding some atypical cases. On the other hand, since SDA diagrams are easily comparable to CAs, it is possible to use them to study the adherence of these health-care procedures to the official standards. We have used an automatic process to compare the health-care procedures of SAGESSA represented with a SDA diagram (whose correctness was previously checked) with the standards defined by ICSI (Schwartz, 2006), SIGN (MacWalter, 2001), NHF (Heart Foundation of Australia (NHF, 2008), and SEH (Española de Hipertensión (SEH), 2005). The highest levels of adherence were obtained for NHF and SEH with 90.4% of treatment coincidence. All the results obtained in this paper have been analyzed and evaluated by medical experts of SAGESSA who have also stated that the SDA diagrams obtained are easy to understand and medically correct. Therefore, the proposed methodology provides a valid tool to automatically induce procedural knowledge as SDA diagrams from health-care EOC databases.

Acknowledgements

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Appendix A. The SDA model

The SDA model (Riaño, 2007) was defined as a combination of all the representation primitives that any CIG system is expected to have (Isern & Moreno, 2008; Mulyar et al., 2007; Peleg et al., 2003; Phil et al., 2002) (i.e., actions, decision, patient states, execution states, sequences, concurrences, alternatives, and loops) with the simplicity of CAs. This model is founded on the concept of *term* or vocabulary item in the medical domain where procedural knowledge is being generated. These terms can be of the sort state, decision, or action. *State terms* define the vocabulary that is used to describe the feasible patient conditions and situations in the area of interest (e.g., terms as "Elevated_Blood_Pressure" or "Following_Drug_Treatment" to establish a differential treatment). *Decision terms* are the terminology that health-care professionals use to condition the sort of treatment to be followed (e.g., terms as "Secondary_Cause_Suspected" or "BP_at_Goal" that may derive the course of professional activities in one direction or another). *Action terms* are the way that medical, surgical, clinical or management activities are defined (e.g., terms as "LifeStyle_Modifications" or "Drug_Therapy" are respective examples of counsel and prescription, which are two of the types of medical actions that may appear in the description of a treatment). State, decision and action terms are employed to construct three sorts of elements that once interconnected they will describe the medical procedure. These elements are, respectively: states, decisions and actions. *States*, which are subsets of state terms, represent patient conditions, situations, or statuses that deserve a particular course of action which is totally or partially different from the actions followed when the patient is in another state, for example, to differentiate between initial treatment and subsequent treatments or between the different stages of a disease. *Decisions* allow the integration of all the variability that a treatment may have by means of conditions on decision terms which represent some of the available information about the patient and the current situation. *Actions*, which are subsets of action terms, constitute the proper health-care activities involved in the health-care procedure represented.

Similar to the CA notation, in the SDA model, states, decisions, and actions are respectively represented as circles, diamonds, and rectangles which are connected with arrows in order to provide a join representation of a health-care procedure, as the one depicted in Fig. 3. A distinction is made between plain connectors, decisional connectors, and otherwise connectors. *Plain connectors* represent evolutions of the health-care procedure that any patient is able to follow. *Decisional connectors* link decisions with other elements, they contain decision terms, and only the patients who meet all the terms in a connector are able to follow this connector. Finally, *otherwise connectors* link decisions with other elements, they are identified with the word 'otherwise', and only the patients who fulfil none of the connectors leaving a decision are able to follow the otherwise connectors of that decision. See, for example in Fig. 3 a transcription of the CA in Fig. 1 to a SDA in which the treatment of all the patients arriving to the initial state evolves across a plain connector to a decision element where only high risk patients may follow the decision connector that leads to lifestyle modifications and drug therapy. The rest of the patients which are not in high risk follow the otherwise connector towards a different treatment. All the initial treatments converge to the intermediate state where all the patients are expected to be after the first encounter with the health-care professional.

Connectors may have time constraints of the form [*min*, *max*]; *min* representing the minimum time the process must stop before following the connector (e.g., wait two hours before measuring BP again to confirm high BP), and *max* the maximum time the process must stop before moving forward in the treatment (e.g., next visit must be scheduled for not later than one week).

The SDA diagram in Fig. 3 was directly constructed by health-care professionals from the CA in Fig. 1. They introduced a differential treatment between the patients that arrive with high BP for the first time (i.e., initial state) and the patients that are already following a treatment for hypertension (i.e., intermediate state). The *decisions* and the *actions* describe the same treatment represented in the CA, except that the assessment of cardiovascular risk appears only once at the beginning of the CA but it is repeatedly considered in the SDA since Fig. 3 represents a long term treatment.

Alternative SDAs on the same sort of treatment of hypertension are possible depending on the states that we want to represent for decisional purposes. For example, a different SDA could be defined if we were interested in the application of this same treatment but considering the states defined by the classification of BP (see table in Fig. 1). That is to say, differential treatments according to the states *normal*, *pre-hypertension*, *stage* 1 hypertension, and *stage* 2 hypertension.

The interpretation of a SDA is as follows: when a patient arrives, all the SDA states whose state terms are observed in the current patient condition are eligible to start the treatment. If several states are eligible, a health-care professional has to choose one of them (this is called type-0 non-determinism). Once this is decided, the connectors are followed until either a non-eligible state is found or a connector with a positive *min* delay is reached. In this process, all the actions of the followed path are the SDA recommendations for the treatment of that patient. When a decision is reached, all the outgoing decision connectors whose decision terms are part of the patient condition are eligible to follow the treatment of that patient. If only one decision connector is eligible, the connector is followed. If there are several eligible connectors, then a health-care professional has to choose one of them to follow the treatment (this is called type-1 non-determinism). If none of them is eligible, but there is an otherwise connector, then this connector is followed. If several otherwise connectors exist, then a health-care professional decides which one is the one to be followed (this is also considered type-1 non-determinism). In case that there are several plain connectors leaving a state or an action, all of them are eligible and it is the health-care professional who has to decide the one to be followed (this is called type-2 non-determinism).

Non-determinism is only observed when there is not a single accepted and evidence-based procedure to deal with a particular situation and the choice criterion between the alternatives is not defined.

Given a patient, the SDA is used to suggest one or more treatments, related to a concrete disease, in an integrated way. Each treatment is composed of the action terms contained in all the actions in one of the paths of the SDA. The possible paths are those starting in the eligible states, continuing through one of the possible sequences of connectors that the patient satisfies, and ending when the path reaches a non-eligible state or a connector with a min value representing a momentary stop in the treatment.

The SDA model (Riaño, 2007) has been tested in the context of the K4CARE project (www.k4care.net) where it has been successfully used to represent different sorts of procedural knowledge in medicine related to 67 health-care services (Valls, Gibert, Sánchez, & Batet, 2010) and 11 chronic diseases (Campana & Riaño, 2008) that are common in home care. These SDAs were used to manage 23 patients during one week at the town of Pollenza (Italy). The pilot was run by one physician in charge, four general practitioners, four nurses, one social worker and one geriatrician, all of them local professionals that were not involved in the K4CARE project. At the end of the experience, the TAM questionnaire (Adams, Nelson, & Todd, 1992) was used to evaluate the perceived usefulness (rated 5.9/7), easiness of use (rated 5.8/7) and attitude towards usage (rated 6/7) of the above mentioned professionals (Tomassini & Campana, 2009).

Appendix A. Comparison of SDAs with CAs

SDAs do not only comply with the representation primitives required to CIGs (Riaño, 2007) (i.e., actions, decision, patient states, execution states, sequences, concurrences, alternatives, and loops), but they also extend the expressiveness and the flexibility of CAs while maintaining their simplicity. The main features of CAs (Hadorn, 1995) can be categorized as summarization, quality improvement, case standardization, precision, and computerization. *Summarization* is the ability of CAs to summarize at a glance the types of patients, as well as the range of management decisions and the strategies addressed in a procedure described in a CPG. *Quality improvement* refers to CAs as elements to improve the quality of CPGs since they have been shown to result in faster learning, higher retention, and better compliance with established practice standards than standard prose text (Hadorn, 1995). *Case standardization* refers to the fact that CAs are focused on the standard typologies of patients described in the CPGs. *Precision* is the ability that, given a certain patient typology, the CA proposes a precise set of actions to be performed. This beneficial feature is sometimes criticized by part of the medical community arguing that CAs impose an excessive rigidity on physicians who share the opinion that patients are too variable in their presentations and preferences to encapsulate them within predefined roadmaps. However, this criticism is diminished by the benefits of CAs. *Computerization* is the feature of CAs of being readily translatable into computerized formats, which permits the systematic application of CPGs recommendations improving the quality of the medical assistance.

SDA diagrams extend the above features with the possibility of representing long term procedures, multiple entry points, multi-term decisions and non-determinism. Firstly, the presence of states for the different stages of a certain disease or disorder lets the SDA model to depict several treatments in an integrated diagram allowing the representation of *long term procedures*. Another feature of the SDA model is that it can deal with *multiple entry points* corresponding to the states that represent the different initial patient conditions and, therefore, not only to integrate the treatment of all these conditions in a single diagram, but also to address each patient directly to the corresponding part of the treatment. SDA diagrams also extend the expressiveness of CAs using *multi-term decisions*. In CAs, decisions are always (Society, 1992) yes-no questions but, in the SDA model, decisions may have more than two branches with different decision terms in each one of them. In addition, each decision may have alternative *otherwise* branches which are followed by the patients that fulfil none of the other branches. This results in a more readable sequence of decisions and also in a more compact representation of treatments. Finally, the rigidity and strictness of CAs, previously referred to as their main criticism, is reduced in the SDA model which increases the flexibility of CAs by dealing with *non-determinism*. Non-determinism is frequent in medicine and it allows the participation of health-care professionals when there is not proven evidence on a unique or better treatment. The SDA model distinguishes between type-0, type-1, and type–2 non-determinisms.

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