OBDD COMPRESSION OF NUMERICAL CONTROLLERS

Giuseppe Della Penna, Nadia Lauri, Daniele Magazzeni Computer Science Department, University of L'Aquila, L'Aquila, Italy

Benedetto Intrigila

Department of Mathematics, University of Roma "Tor Vergata", Roma, Italy

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Abstract: In the last years, the use of control systems has become very common, especially in the *embedded systems* contained in a growing number of everyday products. Therefore, the problem of the *automatic synthesis* of control systems is extremely important. However, most of the current techniques for the automatic generation of controllers, such as *cell-to-cell mapping*, *dynamic programming*, *set oriented approach* or *model checking*, typically generate *numerical controllers* that cannot be embedded in limited hardware devices due to their size.

A possible solution to this problem is to *compress* the controller. However, most of the common lossless compression algorithms, such as LZ77, would decrease the controller performances due to their decompression overhead.

In this paper we propose a new, completely automatic OBDD-based compression technique that is capable of reducing the size of any numerical controller up to a *space savings of 90%* without any noticeable decrease in the controller performances.

1 INTRODUCTION

Control systems (or, shortly, *controllers*) are small hardware/software components that control the behavior of larger systems, the *plants*. A controller continuously looks at the plant *state variables* and possibly adjusts some of its *control variables* to keep the system in the *setpoint*, which usually represents its *correct* behavior.

In the last years, the use of controllers has become very common in robotics, critical systems and, in general, in the *embedded systems* contained in a growing number of everyday products. Therefore, the problem of the *automatic synthesis* of control systems is extremely important.

To this aim, several techniques have been developed, based on a more or less systematic exploration of the plant state space. One can mention, among others, *cell-to-cell mapping* techniques (Leu and Kim, 1998), *dynamic programming* (Kreisselmeier and Birkholzer, 1994) and *set oriented approach* (Grüne and Junge, 2005). Recently, *model checking* techniques have also been applied (Della Penna et al., 2006; Della Penna et al., 2007b) in the field of automatic controller generation.

The controllers generated using all these techniques are typically *numerical controllers*, i.e. tables indexed by the plant states, whose entries are commands for the plant. These commands are used to set the control variables in order to reach the setpoint from the corresponding states. Namely, when the controller reads a state from the plant, it looks up the action described in the associated table entry and sends it to the plant.

However, a main problem of this kind of controllers is the *size* of the table, which for complex systems may contain millions of entries, since it should be embedded in the control system hardware that is usually very limited.

A possible solution to these problems is to derive, from the huge numerical information contained in the table, a small *fuzzy control system*. This solution is natural since fuzzy rules are very flexible and can be adapted to cope with any kind of system. More-

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over, there are a number of well-established techniques to guide the choice of fuzzy rules by statistical considerations, such as in Kosko space clustering method (Kosko, 1992), by abstracting them from a neural network (Sekine et al., 1995), by clustering the trajectories obtained from the cell mapping dynamics (Leu and Kim, 1998) and finally by using genetic algorithms (Della Penna et al., 2007a).

However, two considerations are to be made with respect to this approach. First, the detection of the fuzzy rules requires (at least) a *tuning phase* which is not completely automatic but involves some human intervention. Second, the fuzzy rules appear not to be suitable when a very high degree of precision is needed. This is the case, e.g., of the *truck and trailer parking problem* when *obstacles* are to be avoided in the parking lot (Della Penna et al., 2006). In this case, when the truck is near to an obstacle, only a very precise manoeuvre can park it, without hitting the obstacle. So, to achieve the required precision, an exceeding number of fuzzy rules would be necessary.

Therefore, it seems reasonable to pursue another possible approach, that is *to directly compress the control table*. By this we mean *data compression* in the usual sense of *reduction of the number of bits* needed to represent the controller table in the computer RAM memory (Cover and Thomas, 2006; Nelson and Gailly, 1995).

Observe, however, that in this case the compression algorithm should be constrained as follows:

- the logical content of the table, that is the relation between the states and the corresponding control actions, must be preserved without any loss of information (i.e., we need some kind of *lossless* compression algorithm);
- 2. the access time to the table must be comparable with the one obtained with a direct representation of the table in the computer memory (i.e., the *decompression overhead* must be minimal).

Consider as an example the straightforward idea of directly compressing the table by mean of (some variant of) the well known Lempel-Ziv algorithm (Ziv and Lempel, 1977). Since this is a lossless compression, the first requirement above is fulfilled, but not the second one, since the access time to the table would be linear in the *uncompressed* size of the table itself (Nelson and Gailly, 1995).

Since all the common compression algorithms have similar problems when applied to controllers, we decided to develop a new *ad-hoc* compression algorithm based on the well known *Ordered Binary Decision Diagrams (OBDDs)* (Bryant, 1986).

Decision diagrams as well as *decision trees* are of wide use in data manipulation as well as in data min-

ing (Hand et al., 2001). Indeed, our choice of OB-DDs was motivated by their capability of compressing large state spaces, that is at the hearth of *symbolic model checking* and of its great achievements (Burch et al., 1992; Clarke et al., 1999). Our hypothesis has been that this capability is transferrable to the compression of the controller table which is, in a sense, an augmented state space representation.

Our experimental results show that this is indeed the case. For very large tables we obtain a quite good compression ratio (around 10:1). Moreover, not only the access time is good, but it is often *even better* than the one obtained by a direct representation of the table in memory. This phenomenon is due to the fact that, unless we accept a very sparse table, with huge waste of space, we need to represent the controller using some kind of *open addressing* table accessed through a *hash function*, with a consequent worsening of the access time (Cormen et al., 2001).

A final but very important point to be stressed is that the implemented compression algorithm, which transforms the controller table in an OBDD, operates in a completely automatic way. The only parameter the user should set is the BDD variable reordering method (see Section 4), which can effect the compression ratio. After that, the compression operates in a "zip"-like fashion. However, the best setting of the above parameter can also be discovered by the algorithm by trying all the possible reorderings, thus making the compression process completely automatic. Finally, a further automatic step can also be applied to transform the OBDD into C-code that can be incorporated in any C-program.

The paper is organized as follows: in Section 2 we give a description of OBDDs and in Section 3 we show how we use them to encode numerical controllers. In Section 4 we present our experimental results and Section 5 concludes the paper.

2 ORDERED BINARY DECISION DIAGRAMS

A Binary Decision Diagram (*BDD*) is a data structure used to represent a boolean function (Bryant, 1986). Indeed, any boolean function f can be represented as a binary tree having two kind of leaf values: F(boolean false) or T (boolean true). Each node of the tree (*decision node*) is labeled by a variable of the formula f. The two edges outgoing a decision node represent an assignment of the corresponding variable to false or true, respectively. Therefore, a path from the BDD root to one of its leaves represents a (possibly partial) variable assignment for f, and the corresponding leaf value is the value of f for the given assignment.

An advantage of BDDs is that many logical operations, like conjunction, disjunction, negation or abstraction can be implemented by polynomial-time graph manipulation algorithms. Indeed, BDDs are extensively used in the software tools, e.g., to synthesize circuits or to perform formal verifications.

If variables appear in the same order on all paths (or, in other words, if all the nodes on the same tree level refer to the same variable) the BDD is called *ordered* (OBDD).

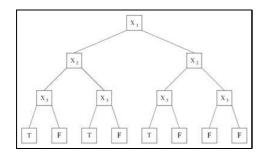


Figure 1: Representation of the boolean function $f(x_1, x_2, x_3) = \bar{x}_1 \cdot \bar{x}_2 \cdot \bar{x}_3 + \bar{x}_1 \cdot x_2 \cdot \bar{x}_3 + x_1 \cdot \bar{x}_2 \cdot \bar{x}_3$.

As an example, Figure 1 shows the OBDD for the boolean function $f(x_1, x_2, x_3) = \bar{x}_1 \cdot \bar{x}_2 \cdot \bar{x}_3 + \bar{x}_1 \cdot x_2 \cdot \bar{x}_3 + x_1 \cdot \bar{x}_2 \cdot \bar{x}_3$.

Usually, OBDDs are also *reduced* (ROBBD) by merging isomorphic subgraphs and eliminating nodes having two isomorphic children. In this way, any boolean formula f can be represented by an *unique* and very compact rooted, acyclic and directed graph.

The size of a reduced BDD is determined both by the function being represented and by the chosen *ordering of the variables*. Thus, a correct variable ordering is of crucial importance to gain the best "reduction factor". The problem of finding the best variable ordering is NP-hard, but there exist efficient heuristics to tackle the problem.

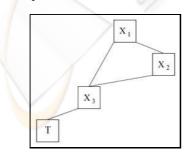


Figure 2: The OBDD in Figure 1 after removal of duplicate nodes and redundant tests.

Figure 2 shows the reduced version of the OBDD

in Figure 1. Note that all the paths leading to F have been actually removed from the graph, since they are simply the complement of those leading to T.

A useful way to see BDDs, that will be used in this paper, is that they *encode the compressed representation of a relation*. However, unlike other compression techniques, the actual operations on BDDs are performed *directly on that compressed representation*, i.e. without decompression. Details on this issue are given in Section 3.

3 BOOLEAN ENCODING OF NUMERICAL CONTROLLERS

OBDDs can be used to create some kind of compressed representation of any data that can be encoded as a *logical expression*. In this Section, we describe how a numerical controller can be seen as a boolean formula, and give details on the actual OBDD-based compression algorithm that has been implemented. Moreover, we give some information on how the OBDD-compressed controller can be efficiently queried and transformed in a hardwareembeddable form.

3.1 Boolean Encoding of the Controller Table

As already said, an OBDD can be actually seen as a compact representation of a relation. On the other hand, a controller table containing a set of (state,action) pairs represents a relation $R = \{(s,a)|a$ is the action associated to *s* in the controller table} between states and actions. Since BDDs encode formulas, it may be useful to represent *R* through its characteristic function C_R defined as follows:

$$C_R(s,a) = \begin{cases} T & \text{if } (s,a) \in R \\ F & \text{otherwise} \end{cases}$$

Now, to write a definition of C_R as a boolean formula, we first have to represent its arguments, i.e., states and actions, in terms of logic variables. To this aim, we expand them to their binary memory representation.

Let suppose that states are *n*-bit values and actions are *m*-bit values. We write s[i] and a[i] to denote the *i*th bit of state *s* and action *a*, respectively.

Let x_i , i = 1...n and y_j , j = 1...m be n+m boolean variables. A state *s* is then be represented by the formula

$$f_s(x_1,\ldots,x_n) = \bigwedge_{i=1\ldots n} l_i \text{ where } l_i = \begin{cases} x_i & \text{if } s[i] = 1\\ \bar{x}_i & \text{if } s[i] = 0 \end{cases}$$

Each f_s is a boolean formula in *n* variables that is true if and only if its variables are assigned with the bits of *s* (denoting, as usual, the boolean true with 1 and the boolean false with 0). In the same way, an action *a* corresponds to the formula

$$f_a(y_1, \dots, y_m) = \bigwedge_{i=1\dots m} l_i \text{ where } l_i = \begin{cases} y_i & \text{if } a[i] = 1\\ \overline{y_i} & \text{if } a[i] = 0 \end{cases}$$

Therefore, the controller characteristic function C_R can be encoded by the boolean formula

$$f_R(x_1,\ldots,x_n,y_1,\ldots,y_m) = \bigvee_{(s,a)\in R} (f_s \wedge f_a)$$

 f_R is a boolean formula in n + m variables that is true if and only if the variable assignment corresponds to the encoding of a (s, a) pair for which R(s, a) holds.

For example, assume that the controller table contains the following 2-bit states s = 00, s' = 01, s'' = 10, with the following associated 1-bit actions u = 0, u' = 0, u'' = 1. Then the formula for the characteristic relation would be $f_R = \bar{x}_1 \cdot \bar{x}_2 \cdot \bar{y}_1 + \bar{x}_1 \cdot x_2 \cdot \bar{y}_1 + x_1 \cdot \bar{x}_2 \cdot y_1$.

3.2 Algorithm for the Logic Encoding of Numerical Controllers

```
BDD BDD_encoding(controller_table CTRL) {
 read number N of entries in CTRL;
 read number n of bits in each state of CTRL;
 read number m of bits in each action of CTRL;
foreach j = 1...n create boolean variable x_j;
 foreach j = 1...m create boolean variable y_j;
 BDD f_R;
 foreach i = 1 \dots N {
  BDD E, f_s, f_a;
  foreach j = 1...n //encode state bits
   if (bit(CTRL[i].state,j) == 1) f_s = f_s \wedge x_j;
   else f_s = f_s \wedge \bar{x_j};
  foreach j = 1...m //encode action bits
   if (bit(CTRL[i].action,j) == 1) f_a = f_a \wedge y_j;
   else f_a = f_a \wedge \bar{y}_j;
  E = f_s \wedge f_a;
  f_R = f_R \lor E; //disjunction of entries
 return f_R; }
```

Figure 3: Algorithm for the logic encoding of numerical controllers.

The encoding algorithm, whose pseudocode is shown in Figure 3, implements the technique described in the previous Section.

After reading the number of bits in the controller states and actions, the BDD_encoding procedure creates the corresponding set of boolean variables x_i and y_i , respectively.

Then, for each entry of the controller table, a new BDD *E* is created as the appropriate conjunction of the state and action variables. In particular, the code checks every bit in the state and adds to the BDD f_s a conjunction with the corresponding variable, in its positive or negated form, based on the value of the bit. The process is then repeated for the action bits in the BDD f_a , and finally *E* is obtained as $f_s \wedge f_a$.

The BDD E is then added to the final BDD f_R using a disjunction. When all the controller entries have been processed, BDD_encoding returns f_R .

As we can see, the algorithm is actually very simple, since all the BDD manipulation is done by the external BDD package. In particular, our implementation uses the CUDD (CUDD Web Page, 2007) BDD manipulation package. Such package provides a large set of operations on BDDs and many variable dynamic reordering methods, which are crucial to gain the highest possible compression factor (Section 2).

Note that, to ensure the correctness of our approach, we also developed a parallel-query algorithm that tests for correctness and completeness the BDD-encoded controller f_R with respect to the original numerical controller *CTRL*. This procedure simply compares the results obtained by querying the uncompressed and the compressed controller with all the states in the controller table.

3.3 Querying the Encoded Controller

Once we have compressed the controller table in a BDD f_R , we must show how this information can be accessed by the controller itself to perform its task. There are several ways to do this.

A first method relies on the fact that the generated BDD actually encodes a function from states to actions. In other words, given a state, there is only one action associated to such state in the controller table. At the BDD level, this means that if we *restrict* the BDD by assigning to the variables $x_1 \dots x_n$ the bits of a particular state *s*, then the resulting BDD has only one *satisfying assignment*, i.e., the one assigning to $y_1 \dots y_m$ the bits of the corresponding action *a*.

Thus the action associated to a state can be found by applying two operations (restriction and then deduction of satisfying assignments) on the BDD of f_R . However, since controllers must work in the quickest and simplest possible way, we may consider an alternative query method that requires less runtime overhead.

From the BDD of f_R , we extract *m* different BDDs $f_R^1 \dots f_R^m$, one for each bit of the action, in the following way.

$$f_{R}^{i}(x_{1},...,x_{n}) = \begin{array}{c} \exists (y_{1}...,y_{i-1},y_{i+1},...,y_{m}) \\ f_{R}(x_{1},...,x_{n},y_{1}...,y_{i-1},1,y_{i+1},...,y_{m}) \end{array}$$

In particular, in each f_R^i we existentially abstract all the action bit variables $y_j, j = 1...m$ except for y_i , which is assigned to the constant 1. The resulting formula f_R^i has *n* free variables $x_1...x_n$, which correspond to the state bits.

If we assign $x_1
dots x_n$ to the binary representation of a state *s*, then f_R^i is true if and only if there exists an action associated to *s* whose *i*th bit is 1. Since the action associated to *s*, if it exists, is unique, f_R^i actually returns the *i*th bit of the action associated to *s* (assuming, as usual, that the logical true and false correspond to the values 1 and 0, respectively).

Having these functions at hand, we can rebuild the binary representation of the action *a* associated to the state *s* by simply applying each f_R^i to the encoding of *s*, without any further runtime BDD manipulation. The execution overhead is minimal in this case, since the "computation" of the BDD value for a particular variable assignment requires only a visit of the associated graph.

3.4 BDD into C Code Translation

Embedding and querying the BDD-compressed numerical controller within a small hardware or software device is also an issue that can be addressed in various ways.

Obviously, we cannot require CUDD or another BDD-manipulation package to be present in the controller. However, a BDD (or the set of BDDs obtained using the technique described in Section 3.3) can be simply translated in a C code fragment composed by nested if-then-else statements.

The translation process is very straightforward and requires only a visit of the OBDD graph. Let *n* be a node of the OBDD associated with the logic variable V(n), and let T(n) and E(n) be the two children of *n* for V(n) = true and V(n) = false, respectively. Then, we can define the C-translation of *n* as follows:

$$CT(n) = \begin{array}{c} \text{IF } (V(n)) \\ \text{THEN } CT(T(n)) \\ \text{ELSE } CT(E(n)) \end{array}$$

This translation is linear in terms of the required space, and the resulting representation can be easily embedded in a (small) hardware device resulting in good time performances.

4 EXPERIMENTAL RESULTS

To setup our experiments, we first have to fix some BDD encoding parameters, namely the variable ordering in the boolean formulas and the dynamic reordering method used by the BDD package.

Indeed, the BDD structure and therefore the compression ratio can be influenced by the original ordering of the variables in the boolean formulas presented to the BDD package. In particular, we recall that the variables in our BDDs are the state bit variables, namely $x_i, i = 1...n$, and the action bit variables, $y_i, i = 1...m$. Thus, we may consider the variable orderings arising from all the possible combinations of the following conditions:

- the state bit variables and the action bit variables can be ordered with different endianness, that is from the most significant bit to the least or viceversa;
- the state bit variables can be placed before the action bit variables, after them or interleaved.

Namely, we can write the function f_R of Section 3 with any of the ten variable orderings O1...O10 shown in Table 1. Note that in O9 and O10 we assume n > m.

01	$x_1 \cdots x_n y_1 \cdots y_m$
02	$x_1 \cdots x_n y_m \cdots y_1$
03	$x_n \cdots x_1 y_1 \cdots y_m$
04	$x_n \cdots x_1 y_m \cdots y_1$
05	$y_1 \cdots y_m x_1 \cdots x_n$
06	$y_1 \cdots y_m x_n \cdots x_1$
07	$y_m \cdots y_1 x_1 \cdots x_n$
08	$y_m \cdots y_1 x_n \cdots x_1$
09	$x_1y_1x_2y_2\cdots x_my_mx_{m+1}\cdots x_n$
010	$x_n, y_m x_{n-1} y_{m-1} \cdots x_{m-n} y_1 x_{m-n-1} \cdots x_1$

Table 1: Possible initial variable orderings.

Moreover, variables can be dynamically reordered by the BDD package during the construction of the final BDD. In our experiments, we used the fourteen dynamic reordering methods $R1 \dots R14$ offered by the CUDD package and shown in Table 2.

In the following experiments we tried all the possible combinations between initial variable orderings and dynamic reordering methods, choosing each time the one that produces the better compression ratio.

All the experiments were performed on a 2.66GHz Pentium 4 with 1GB RAM.

Table 2: CUDD variable reordering methods.	Table 2:	CUDD	variable	reordering	methods.
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R1	Random reordering
R2	Random pivot reordering
R3	Sift
R4	Converging sifting
R5	Symmetric sifting
R6	Converging symmetric sifting
R7	Group sifting
R8	Converging group sifting
R9	Window permutation (size 2)
R10	Window permutation (size 3)
R11	Window permutation (size 4)
R12	Converging window permutation (size 2)
R13	Converging window permutation (size 3)
R14	Converging window permutation (size 4)

4.1 Inverted Pendulum Controller

The first case study is the numerical controller for the inverted pendulum problem (Kreisselmeier and Birkholzer, 1994), where the controller has to bring the pendulum to equilibrium by applying a torque in the shaft.

The optimal numerical controller was generated using the dynamic programming method described in (Kreisselmeier and Birkholzer, 1994). Table 3 shows the details of such controller. In the table, row Entries indicates the number of controller entries (i.e., controlled states) and row Size-column Normal indicates the controller table size in Kilobytes. Moreover, to compare the effectiveness of the BDD compression with respect to the common compression techniques, we also show the size of the controller table compressed by the LZ77-based (Ziv and Lempel, 1977) algorithm of gzip (GZip Web Page, 2007) (row Sizecolumn LZ, where the relative size of the compressed file is also shown as a percentage) and the average controller access time in milliseconds for both the uncompressed and the compressed representations (row Time-column normal and row Time-column LZ, respectively). Note that, as we expect, access times for the LZ-compressed controller are very high since, in the worst case, the controller must be completely decompressed to find the required table entry.

Table 3: Numerical controller for the inverted pendulum.

	Normal	LZ		
Entries	311618			
Size	3043	1295 (42.6%)		
Time	8 ms	657 ms		

When BDD compression is applied to the controller, we obtain BDDs whose size (in number of graph nodes) is shown in Table 4 for each combination of variable initial ordering (O1...O10) and dynamic reordering (R1...R14).

Here, the smallest BDD (indicated by the bold number in Table 4) has 61584 nodes. The actual size in Kilobytes and the average access time for the BDD-compressed controller are shown in Table 5. As we can see, BDD compression reduces the controller 26.5% more than LZ, and has also better access times than the LZ-compressed version, since it does not require any decompression to read the table entries.

Table 5: BDD-compressed numerical controller for the inverted pendulum.

	BDD
Entries	311618
Size	489 (16.1%)
Time	1 ms

4.2 Truck and Trailer Obstacles Avoiding Controller

In the second case study, we consider the controller for the *truck and trailer obstacles avoiding* problem. Namely, the controller has to back a truck with a trailer up to a specified parking place starting from any initial position in the parking lot. Moreover, the parking lot contains some obstacles, which have to be avoided by the truck while maneuvering to reach the parking place. Corrective maneuvers are not allowed, that is the truck cannot move forward to *backtrack* from an erroneous move.

Table 6: Results for the truck and trailer obstacles avoiding controller.

	Normal		
Entries		3256855	
Size	71650	22644 (31.6%)	7038 (9.8%)
Time	89 ms	3173 ms	108 ms

The numerical controller was generated with the CGMur ϕ tool (CGMurphi Web Page, 2006; Della Penna et al., 2007b). Results are in Table 6. As we can see, the controller has a very big size. However, the best BDD compression scheme (O5,R5) is able to reduce the size of the controller up to a 90.2% space savings, that is 21.8% more than using LZ77 compression. Moreover, the BDD compression continues to win also with respect to the access times.

	01	02	03	O4	05	06	O7	08	O9	010
R1	92490	108474	65382	64012	156872	83808	149943	86957	92013	145877
R2	142012	145654	66711	78029	130315	79575	144583	89528	148037	142432
R3	65842	61588	65842	61584	138377	75360	145181	143181	65854	127241
R4	65842	71314	70691	61584	130355	71313	75427	135580	65842	65843
R5	65842	65848	70774	70770	144310	70773	144422	70776	65865	142677
R6	65842	65860	70777	70770	135575	70773	135573	70773	65860	130348
R7	66759	66555	92830	61798	144268	61586	136870	61594	69198	65865
R8	65842	61594	75420	61584	145172	61586	135575	61586	65868	65863
R9	92295	92279	65441	61873	163149	121083	255309	121307	101164	178482
R10	76724	77231	61584	61588	134758	122539	143860	78044	79227	142072
R11	72724	72781	61584	61584	134023	122157	134254	106597	77295	134723
R12	81329	98992	61630	61641	134162	128731	138481	79723	86284	136761
R13	77034	65868	61584	61584	134023	123547	134275	111460	66122	134257
R14	65842	65868	61584	61584	134275	77960	134275	116568	68455	134079

Table 4: Number of nodes in the BDD for the inverted pendulum controller with respect to different variable orderings.

4.3 Inverted Pendulum on a Cart Controller

The last case study is the numerical controller for the inverted pendulum on a cart problem (Junge and Osinga, 2004). The system consists of a planar inverted pendulum on a cart that moves under an applied horizontal force, constituting the control. The position of the pendulum is measured relative to the position of the cart as the offset angle from the vertical upright position. The controller goal is to set such angle to zero.

Table 7: Results for the inverted pendulum on a cart controller.

	Normal	LZ	BDD
Entries		151394	
Size	1478	90 (6.1%)	215 (14.6%)
Time	3 ms	206 ms	1 ms

The numerical controller was generated with the CGMur ϕ tool. Results are in Table 7. The number of controller entries is very small with respect to the previous two case studies. We see that on a small controller the BDD compression has a lower compression ratio than LZ, but always better access times (1ms vs. 206ms), since it does not require any decompression to read the table entries.

5 CONCLUSIONS

In this paper, we presented an OBDD based compression algorithm for numerical controllers. The compression algorithm is completely automatic and can be applied to the (state, action) tables generated by any numerical controller generation technique.

Our experiments show that this new algorithm has a very high compression ratio (up to 10:1), that is often more than the ratio obtained on the same data by the most common lossless compression techniques, such as LZ77. Indeed, OBDD compression is not actually lossless, but rather "relation-invariant". That is, the OBDD compression leaves intact the behavior of the state-action relation stored in the table. However, by working on the logic encoding of the relation, the OBDD is capable of *optimizing the representation of the relation*, so reducing its size.

Moreover, accessing the entries of an OBDDcompressed numerical controller does not require any data decompression (as it would happen, e.g., with LZ77), so the controller performances are very good. Also in this case, the optimized representation generated by the OBDD sometimes allows to achieve access times that are even better that those of an hash function used on the uncompressed table.

Therefore, the BDD compression is a technique that can be actually exploited to reduce the size of numerical controllers, generating a compact structure that is easy to store and query. This would allow, e.g., to use *high precision controllers* even in *limited devices*.

Indeed, we are currently studying and implementing algorithms that create *embeddable and executable* forms of the OBDD-compressed controllers. The OBDD-to-C methodology sketched in section 3.4 is only the first step, as we intend to design a translation process to directly create an optimized VHDL (Pedroni, 2004) circuit description from the OBDD. In this way, we would have a completely automatic methodology to generate, from any numerical controller, a small executable definition ready to be embedded in the hardware.

Finally, a last point we want to investigate is the relationship between the compression obtained with the use of the OBDDs and the reduction of fuzzy control systems by means of a *hierarchical* approach (see e.g. (Stufflebeam and Prasad, 1999)). Indeed, there is an evident correspondence between, on one hand, the search of the best ordering of variables needed for the OBDD compression and, on the other, the hierarchical decomposition into subsystems of a fuzzy system.

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