

Fuzzy Rule Interpolation in Embedded Behaviour-based Control

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Abstract— Fuzzy Rule Interpolation (FRI) methods are efficient structures for knowledge representation with relatively few rules. In spite of the good knowledge representation efficiency, the usually high computational demand turns the FRI methods hardly suitable for embedded real-time applications, where the short reasoning time has a high importance. On the other hand the fact of increasing computational power of nowadays available devices gives an opportunity to the FRI methods for appearance in real-time embedded applications. The goal of this paper is to introduce the benefit of adapting low computational and resource demanded FRI methods in embedded behavior-based control applications.

Keywords - fuzzy rule interpolation (FRI); low computational demand FRI; fuzzy automata; behavior-based control.

I. INTRODUCTION

The idea of behavior-based control is in a great extent originated from the existence of descriptive verbal models based on numerous observations of living creature's reactions in different situations. Many of them are built around a predefined sequence of environmental situations and events, where the reactions are in details noted and evaluated. The knowledge representation in this case is a series of observations of various facts and action-reaction rules. For mathematical modeling of such a system, the rule-based knowledge representation is straightforward. Moreover the need of following observed sequences requires a model structure of a state machine or an automaton. Adding the fact, that the observable or hidden states are continuous measures, the situation is quite complicated. Summarizing the above requirements, the model has to have a rule-based knowledge representation, and the ability of describing event sequences of continuous values and continuous states. The suggested modeling method is the adaptation of the fuzzy automaton, where the state is a vector of membership values, the state-transitions are controlled by a fuzzy rule-base and the observations and conclusions are continuous values. The main problem in case of practical implementation of such a fuzzy automaton based model is the size of the state-transition rule base. In classical fuzzy reasoning the rule base size is exponential with the number of observations, in this case with the length of the state vector. In case of a behavior-based control model of moderate complexity it could be 10-20 state variables i.e. thousands of rules required for the complete

classical rule base (e.g. the Zadeh-Mamdani-Larsen Compositional Rule of Inference (CRI) (Zadeh [1]) (Mamdani [2]) (Larsen [3]) or the Takagi-Sugeno fuzzy inference (Sugeno [4], Takagi-Sugeno [5])).

Moreover, having a verbal model, the existing knowledge is usually a few dozen verbal rules, which means, that most of the rules are undefined. In case of classical fuzzy reasoning this contradiction is hardly solvable.

The solution suggested in this paper for the exponential complexity problem of the required fuzzy automation state-transition rule base is the application of the Fuzzy Rule Interpolation (FRI) methods (one of the first methods was introduced in [6]). By the application of FRI methods the number of the rules required for the FRI state-transition fuzzy model can be reduced to the existing (known from the verbal model) rules. Moreover in case of automatic model generation or fine tuning based on given input-output sample data, the application of the FRI model can also lead to fewer rules and hence less parameters, which means better convergence of the optimization algorithm.

The behavior-based model implementation introduced in this paper is built upon the framework of fuzzy automaton and low computational demand Fuzzy Rule Interpolation (FRI) [7], [8], [9], and [10]. The knowledge representation style of FRI method fits well the conceptually "sparse rule-based" structure of the descriptive verbal models, where the "completeness" of the rule-base is essentially not required. FRI methods can provide reasonable (interpolated) conclusions even if none of the existing rules fires under the current observation. From the beginning of 1990s numerous FRI methods have been proposed [11].

II. FUZZY RULE INTERPOLATION (FRI)

Traditional fuzzy rule based systems (e.g. the Zadeh-Mamdani-Larsen CRI ([1], [2], [3]) or the Takagi-Sugeno fuzzy inference ([4], [5]) requires a complete rule base with all of the possible rules set, even though lots of these rules are unimportant from the viewpoint of the actual application. A fuzzy rule base is called sparse or incomplete if an observation may exist, which does not hit any of the rules in the rule base. Accordingly there can be observations, where no conclusion can be gained with traditional fuzzy reasoning techniques. On

the other hand, in many embedded control application areas having no conclusion is an avoidable situation. One real solution for the sparse rule base is the application of fuzzy rule interpolation (FRI) methods. This case the derivable rules are intentionally missing from the rule base, as FRI methods are capable of providing reasonable (interpolated) conclusions even if none of the existing rules fire under the current observation. The FRI rule base could contain the most significant fuzzy rules alone without risking the chance of having no conclusion for some of the observations. In this case having an efficient knowledge representation, a considerable amount of unnecessary work can be avoided during the rule base creation. On the other hand most of the FRI methods are sharing the burden of high computational demand, e.g. the task of searching for the two closest surrounding rules to the observation, and calculating the conclusion at least in some characteristic α -cuts. Moreover in some methods the interpretability of the fuzzy conclusion gained is also not straightforward [12]. There have been a lot of efforts to rectify the interpretability of the interpolated fuzzy conclusion [13]. In [14] Baranyi *et al.* give a comprehensive overview of the recent existing FRI methods. Beyond these problems, some of the FRI methods are originally defined for one dimensional input space, and need special extension for the multidimensional case (e.g. [15], [16]). In [11] Wong *et al.* gave a comparative overview of the multidimensional input space capable FRI methods. In [15] Jenei introduced a way for axiomatic treatment of the FRI methods. In [17] Johanyák introduces an automatic way for sparse fuzzy model identification from sample data. The high computational demand, mainly the search for the two closest surrounding rules to an arbitrary observation in the multidimensional antecedent space makes many of these methods hardly suitable for real-time applications. Some FRI methods, (e.g. the method introduced by Jenei *et al.* in [16], or FRIPOC [18]), eliminate the search for the two closest surrounding rules by taking all the rules into consideration, hence speeding up the reasoning process. On the other hand, keeping the goal of constructing fuzzy conclusion, and not simply speeding up the reasoning process, they still require some additional (or repeated) computational steps for the elements of the level set (or at least some relevant α levels). An application oriented aspect of the FRI, the low computational and resource demand is emerging in the concept of ‘FIVE’ (Fuzzy Interpolation based on Vague Environment). In the followings some details of this method will be briefly introduced.

III. FRI BASED ON VAGUE ENVIRONMENT: FIVE

In the concept of ‘FIVE’ an application oriented aspect, the need for low computational and resource demand has a high importance. The method was originally introduced in [7], [8], [9], and extended in [10] for satisfying the speed requirements of direct fuzzy control, where the conclusions of the fuzzy controller are applied directly as control actions in a real-time system.

The main idea of FIVE is based on the fact that most of the control applications serves crisp observations and requires crisp conclusions from the controller. Adopting the concept of the Vague Environment (VE) [19], FIVE can handle the antecedent

and consequent fuzzy partitions of the fuzzy rule base by scaling functions [19] and therefore turn the fuzzy interpolation to crisp interpolation. The idea of a VE is based on the indistinguishability of elements. In VE the fuzzy membership function $\mu_A(x)$ is indicating level of similarity of x to a specific element a which is a representative or prototypical element of the fuzzy set $\mu_A(x)$, or, equivalently, as the degree to which x is indistinguishable from a (see e.g. on Figure 1) [19]. Two values in a VE are ε -indistinguishable if their distance is less or equal than ε . The distances in a VE are weighted distances (1). The weighting factor or function is called scaling function (factor) [19]:

$$\delta_s(a, b) = \left| \int_a^b s(x) dx \right| \leq \varepsilon, \quad (1)$$

where $\delta_s(a, b)$ is the scaled distance of the values a, b and $s(x)$ is the scaling function on X .

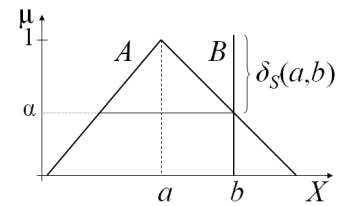


Figure 1. The α -cuts of $\mu_A(x)$ contain the elements that are $(1-\alpha)$ -indistinguishable from a .

If the VE of a fuzzy partition (the scaling function or at least the approximate scaling function [7], [8], [9]) exists, the member sets of the fuzzy partition can be characterized by points in that VE (see e.g. exact scaling function s on Figure 2 and an approximate scaling function on Figure 3).

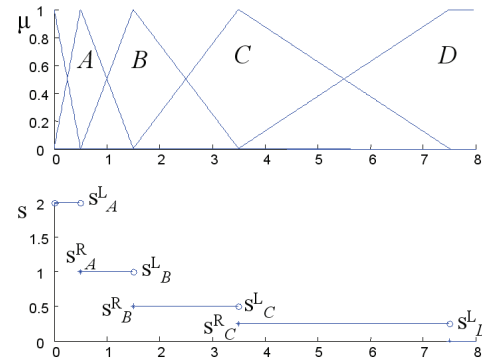


Figure 2. A Ruspini fuzzy (A, B, C, D) partition and its scaling function s .

Having the VE concept and the scaling function based similarity calculation, any crisp interpolation, extrapolation, or regression method can be adapted very simply for FRI [7], [8], [9]. Because of its simple multidimensional applicability, in FIVE the Shepard operator based interpolation (first introduced in [20]) is adapted (see e.g. Figure 4).

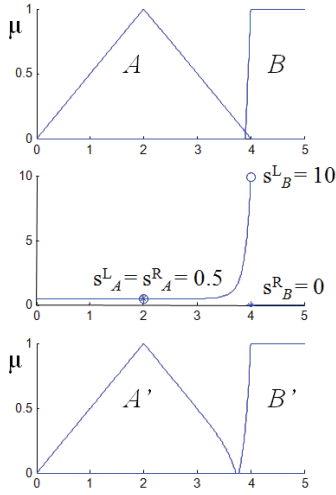


Figure 3. A fuzzy partition (A, B) , its approximate scaling function s [7], [8] and the corresponding approximated partition (A', B') .

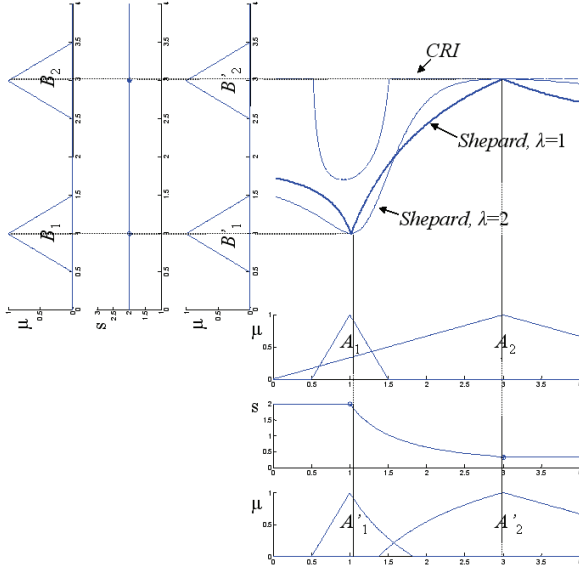


Figure 4. Interpolation of two fuzzy rules ($R_i: A_i \rightarrow B_i$), by the Shepard operator based FIVE (3), and for comparison the min-max CRI with centre of gravity defuzzification.

In case of singleton rule consequents (c_k) the fuzzy rules R_k has the following form:

$$\text{If } x_1 = A_{k,1} \text{ And } x_2 = A_{k,2} \text{ And } \dots \text{ And } x_m = A_{k,m} \quad (2) \\ \text{Then } y = c_k$$

Adapting the VE concept and the scaling function based similarity calculation to the Shepard operator based interpolation, the conclusion of the interpolative fuzzy reasoning can be obtained as:

$$y(\mathbf{x}) = \begin{cases} c_k & \text{if } \mathbf{x} = \mathbf{a}_k \text{ for some } k, \\ \left(\sum_{k=1}^r c_k / \delta_{s,k}^\lambda \right) / \left(\sum_{k=1}^r 1 / \delta_{s,k}^\lambda \right) & \text{otherwise.} \end{cases} \quad (3)$$

where $\delta_{s,k}$ are scaled distances:

$$\delta_{s,k} = \delta_s(\mathbf{a}_k, \mathbf{x}) = \left[\sum_{i=1}^m \left(\int_{a_{k,i}}^{x_i} s_{X_i}(x_i) dx_i \right)^2 \right]^{1/2}, \quad (4)$$

and s_{X_i} is the i^{th} scaling function of the m dimensional antecedent universe, $\mathbf{x}$ is the m dimensional crisp observation and $\mathbf{a}_k$ are the cores of the m dimensional fuzzy rule antecedents A_k .

The code of the FIVE FRI together with other FRI methods is freely available as a MATLAB FRI Toolbox [21], and it can be downloaded from [22] and [23].

IV. FRI BASED FUZZY AUTOMATON

There are numerous versions and understanding of the fuzzy automaton can be found in the literature (a good overview can be found in [24]). In our case we start from the most common definition of Fuzzy Finite-state Automaton (FFA, summarized in [24]), where the FFA is defined by a tuple (according to [24], [25] and [26]):

$$\tilde{F} = (Q, \Sigma, \delta, R, Z, \omega), \quad (5)$$

where

Q is a finite set of states, $Q = \{q_1, q_2, \dots, q_n\}$.

Σ is a finite set of input symbols, $\Sigma = \{a_1, a_2, \dots, a_m\}$.

$R \in Q$ is the (possibly fuzzy) start state of $\tilde{F}$.

Z is a finite set of output symbols, $Z = \{b_1, b_2, \dots, b_n\}$.

$\delta: Q \times \Sigma \times Q \rightarrow [0, 1]$ is the fuzzy transition function which is used to map a state (current state) into another state (next state) upon an input symbol, attributing a value in the fuzzy interval $[0, 1]$ to the next state.

$\omega: Q \rightarrow Z$ is the output function which is used to map a (fuzzy) state to the output.

Extending the concept of FFA from finite set of input symbols to finite dimensional input values turns to the following:

$$\tilde{F} = (S, X, \delta, P, Y, \omega), \quad (6)$$

where

S is a finite set of fuzzy states, $S = \{\mu_{s1}, \mu_{s2}, \dots, \mu_{sn}\}$.

X is a finite dimensional input vector, $X = \{x_1, x_2, \dots, x_m\}$.

$P \in S$ is the fuzzy start state of $\tilde{F}$.

Y is a finite dimensional output vector, $Y = \{y_1, y_2, \dots, y_l\}$.

$\delta: S \times X \rightarrow S$ is the fuzzy state-transition function which is used to map the current fuzzy state into the next fuzzy state upon an input value.

$\omega: S \times X \rightarrow Y$ is the output function which is used to map the fuzzy state and input to the output value. See e.g. on Figure 5.

In case of fuzzy rule based representation of the state-transition function $\delta: S \times X \rightarrow S$, the rules have $n+m$ dimensional antecedent space, and n dimensional consequent space. Applying classical fuzzy reasoning methods, the complete state-transition rule base size can be approximated by the following formula:

$$|R| = n \cdot i^n \cdot j^m, \quad (7)$$

where n is the length of the fuzzy state vector S , m is the input dimension, i is the number of the term sets in each dimensions of the state vector, and j is the number of the term sets in each dimensions of the input vector.

According to (7) the state-transition rule-base size is exponential with the length of the fuzzy state vector and the number of the input dimensions.

Applying FRI methods for the state-transition function fuzzy model can dramatically reduce the rule base size. See e.g. [27], where the originally exponential sized state-transition rule base of a simple heuristic model turned to be polynomial thanks to the FRI.

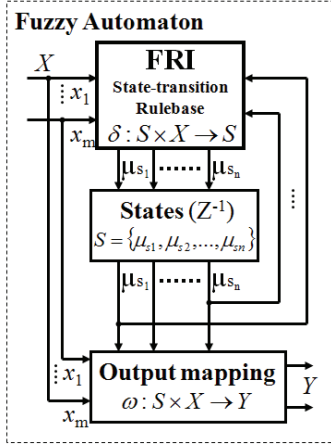


Figure 5. FRI based Fuzzy Automaton.

V. BEHAVIOUR-BASED CONTROL

In behaviour-based control systems (a good overview can be found in [28]), the actual behaviour of the system is formed as one of the existing component behaviours (which fits best the actual situation), or a kind of fusion of the component behaviours appeared to be the most appropriate to handle the actual situation. Beyond the construction of the component behaviors, this structure has two main tasks. The first is the behavior coordination, the decision, which component behavior is needed, or in cases of behavior fusion the determination of

the weights for each component behaviors in solving the actual situation. The second is the way of the behavior fusion.

In case of direct application of the suggested FRI based Fuzzy Automaton for behaviour-based control structures, the output function $\omega: S \times X \rightarrow Y$ can be decomposed to parallel component behaviors and independent behavior fusion. This case we can get a very similar structure as it is expected in behaviour-based control (see Figure 6).

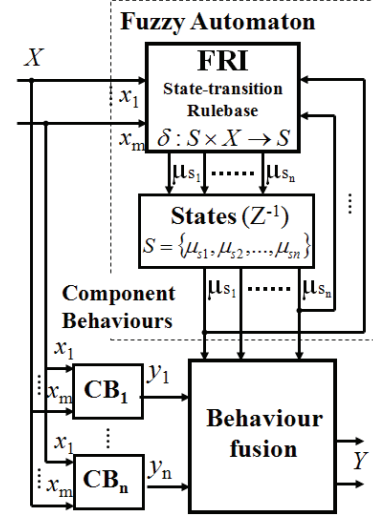


Figure 6. The suggested FRI behaviour-based structure.

VI. NAVIGATION EXAMPLE

The application example of the proposed structure is a simulated steering control of an automated guided vehicle (AGV) already introduced more detailed in [29], [30].

The reason of the application example in this paper is a demonstration for the simple state-transition FRI rule base creation concept, not for competing in collision avoidance performance with other solutions.

In the example application the steering control has two main goals, the path tracking (to follow a guide path) and the collision avoidance. The simulated AGV is first trying to follow a guide path with minimal path tracking error, and in the case if it is impossible (because of the obstacles) leave it, and as the collision situation is avoided try to find the guide path and follow it again (see Figure 8).

In the collision avoidance strategies, two different collision situations, the frontal and the side collision are distinguished. Having the preconditions of motionless obstacles, it is sufficient to have three ultrasonic distance sensors (on the front of the AGV, one in the middle (U_M) and one on both sides (U_L , U_R) (see Figure 7)) to approximate both the collision conditions [30].

In the example, there are four different component behaviours:

Path tracking and restricted collision avoidance strategy: The main goal of this strategy is following the guide path and

as a sub goal, avoiding obstacles if it is possible without risking the chance of losing the guide path [30].

The collision avoidance strategy: A simple collision avoidance steering strategy. Its only goal is to avoid collisions.

The collision avoidance with left/right tendency strategy: The same as the collision avoidance steering strategy, except the left or right turning tendencies in case of no left or right turning difficulties. These strategies are needed to aid finding the path after leaving it.

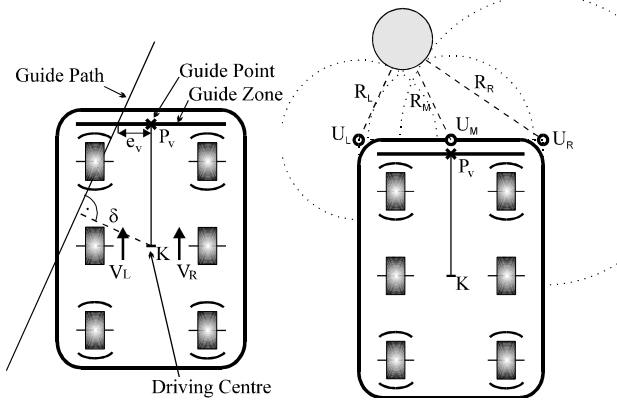


Figure 7. Differential steered AGV with guide zone, e_v is the distance of the guide path and the guide point, P_v is the guide point, K is the driving centre, R_L , R_R , R_M are the distances measured by the left, right and middle ultrasonic sensors (U_L , U_R , U_M).

Having four known component behaviours, the automaton has four state variables (see Figure 6). These are the weight for the path tracking and restricted collision avoidance strategy (S_p), the weight for the collision avoidance strategy (S_c), the weights for the collision avoidance strategy with right tendency (S_{CR}), and for the left tendency (S_{CL}). Having four conclusions, four state-transition rule bases are needed. The R_{SP} state-transition rule base is determining the next value of the S_p state variable, R_{SC} is for determining S_c , R_{SCR} for S_{CR} , and R_{SCL} for S_{CL} .

The observations of the state-transition rule bases are the distance between the guide path and the driving centre (e_v), the distance measured by the middle ultrasonic sensor (R_M) (see Figure 7), the approximated maximal left and right turning angle without side collision (α_{ML} , α_{MR}), the previous state variables (S_p , S_{CR} , S_{CL}), and the availability of path sensing (P_V).

The rules of the state-transition rule bases have the following common form ($R_{S_{X,i}}$):

If $S_p=A_{1,i}$ **And** $S_{CR}=A_{2,i}$ **And** $S_{CL}=A_{3,i}$ **And** $e_v=A_{4,i}$ **And** $P_V=A_{5,i}$ **And** $R_M=A_{6,i}$ **And** $\alpha_{ML}=A_{7,i}$ **And** $\alpha_{MR}=A_{8,i}$ **Then** $S_X=B_i$.

The state-transition rule bases for the FRI fuzzy automaton are summarized in Tab. 1.

Figure 8 and Figure 9 introduces some results of the simulated application (see more detailed in [30]). The results on Figure 9 shows, that in the tested situation the suggested FRI based Fuzzy Automaton behavior coordination was able to follow the state changes in acceptable level.

TABLE I. STATE-TRANSITION RULE BASES

R_{SP} :								
S_p	S_{CR}	S_{CL}	e_v	P_V	R_M	α_{ML}	α_{MR}	S_p
			Z	V	L			L
			PL	V			S	Z
			NL	V		S		Z
			NV					Z

R_{SC} :								
S_p	S_{CR}	S_{CL}	e_v	P_V	R_M	α_{ML}	α_{MR}	S_p
				V	S			L
				V	L			Z
				NV				Z

R_{SCR} :								
S_p	S_{CR}	S_{CL}	e_v	P_V	R_M	α_{ML}	α_{MR}	S_p
L			NL	V				L
	L			NV				L
			Z	V	L			Z
		L						Z

R_{SCL} :								
S_p	S_{CR}	S_{CL}	e_v	P_V	R_M	α_{ML}	α_{MR}	S_p
L			PL	V				L
		L		NV				L
			Z	V	L			Z
	L							Z

where the linguistic labels of the antecedent and consequent fuzzy sets are stand for N : negative, P : positive, VL : very large, L : large, S : small, Z : zero, V : path valid, NV : path not valid.

VII. CONCLUSION

The application of the suggested FRI based Fuzzy Automaton in embedded behavior-based control applications can dramatically simplify the state-transition rule base creation. In case of the simple example of the paper, the R_{SP} rule base has only 4 rules, while the complete rule base should have at least $5 \cdot 2 \cdot 2 \cdot 2^2 = 80$, R_{SCR} and R_{SCL} has 4 rules, while their complete counterpart has at least $2^3 \cdot 5 \cdot 2 \cdot 2 = 160$.

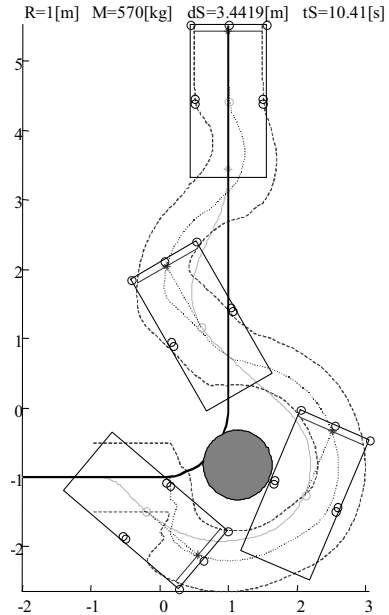


Figure 8. Track of a single run in case of one obstacle.

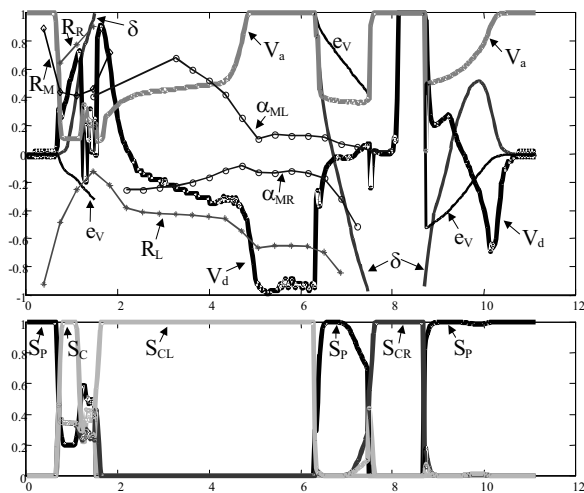


Figure 9. Time function of observations, conclusions and system state values (S_P , S_C , S_{CL} , S_{CR}) related to the track of Figure 8.

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