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Fuzzy model reference control with adaptation mechanism

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ABSTRACT

An improved approach to adaptation in fuzzy model reference learning control (FMRLC) will be introduced in this paper. The main idea of the presented method consists in including into adaptation process the input membership functions in the fuzzy controller. In comparison with original FMRLC algorithm the proposed method can be started with smaller number of input membership functions and reduces amount of penalization after few steps that results in convergent rule base and better and more reliable behavior of the closed loop that is shown on an simulation example of control of a nonlinear time-varying system.

1. Introduction

The fuzzy controllers proved to be convenient for control of systems where a precise model is not available or is highly nonlinear. Nevertheless, classical fuzzy control fails in the case that the plant parameters vary significantly. In such case an automatic process of an adjustment of the rules and/or the fuzzy sets is required.

A fuzzy controller becomes self-organizing, self-learning or self-tuning if it is able to adjust the control rules from past experience without human intervention. The first self-organizing fuzzy controller was worked out in Mamdani and Procyk (1979) and further elaborated in Shao (1988). Unfortunately usability of that approach was limited to small class of plants because of difficult design for tracking reference signals different from a step signal. This drawback was eliminated by fuzzy model reference learning control (FMRLC) algorithm which was for the first time introduced in Layne and Passino (1992). The main idea is based on the conventional *model reference adaptive control* approach (MRAC) (see Åström and Wittenmark (2008)).

During the past several years self-organizing or self-tuning approach has attracted considerable attention in control theory because of its significant theoretic and practical value. This trend is proved by wide range of control applications, e.g. in biomedical engineering (Shieh et al., 2006), in automotive industry (Sharkawy, 2010), in area of actuator mechanisms (Wai et al., 2002) or in chemical engineering (Babuška et al., 2010). Possibilities of implementation of self-organizing controllers in PLC are analyzed e.g. in Bogdan et al. (2007).

Self-learning concept of the FMRLC seems to have great potential that is supported by some successful applications in aeronautics (Layne and Passino, 1996; Yuan, Feng et al., 2004; Yuan, Sun et al., 2004), control hydraulic units (Cerman and Hušek, 2012; Liao, 2006; Ling, 2009; Aly et al., 2003), control of manipulators (Moudgal et al., 1995; Sheppard and Tarbouchi, 2004; Testi et al., 2004), induction machines or generators (Rehman and Dhaouadi, 2008; Ndubisi, 2008; Rehman and Mahmood, 2006; Zhen and Xu, 2000), smart materials and structure (Mayhan and Washington, 1998; Oh and Kim, 2004) or in transportation (Layne and Passino, 1993; Layne et al. (1993)). Other areas of using FMRLC are analyzed e.g. in Cerman and Hušek (2010), Hušek (2012), Ismail (1998), Naceri et al. (2007), Oltean et al. (2007), Su et al. (2005), Xu and Pan (2008), or Zhang et al. (2006). Some improvements of the method one can find especially in Kwong and Passino (1996) with an application in Dessouky and Tarbouchi, 2000. Different approaches to adaptive fuzzy control can be found in Hung et al. (2007), Hušek (2011b), Lian (2012), Hušek (2011a) or Onieva et al. (2013). FMRLC can be used suitably for a class of multi input multi output (MIMO) systems (see e.g. Kwong and Passino (1996)) too.

In this article an application of innovated FMRLC method using splitting and merging the input fuzzy sets during the process of adaptation will be presented. Such approach makes the evolution of rule base convergent. Moreover the proposed method is able to appropriately shape the control surface in the important regions that results in better closed loop responses in comparison with the original FMRLC method.

2. Short introduction to original FMRLC

In the section the FMRLC method will be briefly described, more details can be found in Passino and Yurkovich (1998). The basic scheme of the FMRLC with a fuzzy PD controller and single input single output (SISO) system is shown in Fig. 1. It consists of four main parts: the fuzzy controller to be tuned, the plant, the

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reference model and the learning (adaptation) mechanism. Let us describe the role of each component.

2.1. The fuzzy controller

The inputs to the fuzzy controller are the control error $e_r(kT) = r(kT) - y(kT)$ and the change in error $c_e(kT) = \frac{e_r(kT)-e_r(kT-T)}{T}$, the output from the controller is $u_c(kT)$ where T is the sampling period and k is time sample. Generally, the structure and the inputs to the fuzzy controller can be chosen arbitrarily.

For fuzzy controller design, the scaling gains g_{e_r} and g_{c_e} are used to normalize the universe of discourse for the error $e_r(kT)$ and change in error $c_e(kT)$ to the interval $[-1,1]$, respectively, whereas gain g_u is used for obtaining the actual controller output $u_c(kT)$. The scaled inputs to the fuzzy controller are given by $e(kT) = g_{e_r} e(kT)$ and $c(kT) = g_{c_e} c_e(kT)$ and the real output from the controller by $u_c(kT) = g_u u(kT)$ where $u(kT)$ is the scaled output. These gains are usually tuned within the overall FMRLC initialization.

The rule base for the fuzzy controller has the rules in the following form:

If e is E_o **and** c is C_p **Then** u is U_q

where e and c denote the normalized variables associated with the error and change in error, respectively, u denotes the normalized controller output, E_o and C_p denote the oth (pth) fuzzy set associated with e (c), respectively, and U_q denotes the qth fuzzy set associated with the output.

The input fuzzy sets are defined to characterize the premises of the controller rules and their shape and position remain fixed during the whole control process. The position of the output fuzzy sets is assumed to be unknown and will be synthesized or tuned automatically. In the fuzzy controller uniformly distributed, symmetric triangular fuzzy sets are usually used for both input universes of discourse. Although arbitrary shapes of the output fuzzy sets can be chosen the singletons are sufficient in most applications. At the beginning of adaptation the position of all of them is usually supposed to be at zero but a different initialization can be set up.

2.2. The reference model

The reference model defines closed loop specifications (such as stability, rise time, and overshoot) and generates the desired trajectory. Similarly to conventional MRAC the learning mechanism modifies the fuzzy controller so that the closed loop system behaves like the given reference model. The reference model has to be chosen reasonably because if the requirements are too strong the adaptation mechanism shifts the output fuzzy sets by large steps which can cause loss of stability.

2.3. Learning mechanism

The learning mechanism modifies the rules in the fuzzy controller so that the closed loop system behaves like the reference model, i.e. it aims at decreasing the deviation from the desired behavior $y_e(kT)$. It consists of two parts (see Fig. 1): *the fuzzy inverse model* and *the knowledge-base modifier*. The fuzzy inverse model transforms $y_e(kT)$ to changes $p(kT)$ in the process inputs $u(kT)$ that are necessary to force $y_e(kT)$ to zero. Knowledge-base modifier brings this change into effect by shifting by $p(kT)$ the output membership function of the rule that acted with the highest strength at the time instant $kT - T_d$ where T_d is the delay of the plant.

Note that analogically to the fuzzy controller, the fuzzy inverse model contains normalizing scaling factors, namely g_{y_e}, g_{y_c}, g_p, for each universe of discourse.

Let us recall that the original FMRLC method tunes only the position of output fuzzy sets. Other parameters of the controller are not changed during adaptation. Unfortunately, such arrangement is not able to meet strict requirements on closed loop behavior that puts serious limitations on control applications. The main reason is that a fixed partitioning of the input controller subspace does not allow appropriate shaping of the controller surface in different regions that is necessary because of nonlinear nature of the plant.

3. Fuzzy model reference control with adaptation of input fuzzy sets

One solution of the above mentioned problem consists in increasing the number of input fuzzy sets and consequently the number of the rules. However in that case numerical complexity as well as the time required for adaptation of all rules grow considerably. The procedure proposed in the paper copes with that problem by modification of the input fuzzy sets.

There are several possibilities how to tune input fuzzy sets: shifting, changing the shapes or changing their number. Shifting and changing the shape of original fuzzy sets are not suitable since it causes modification in all rules which share the same input fuzzy

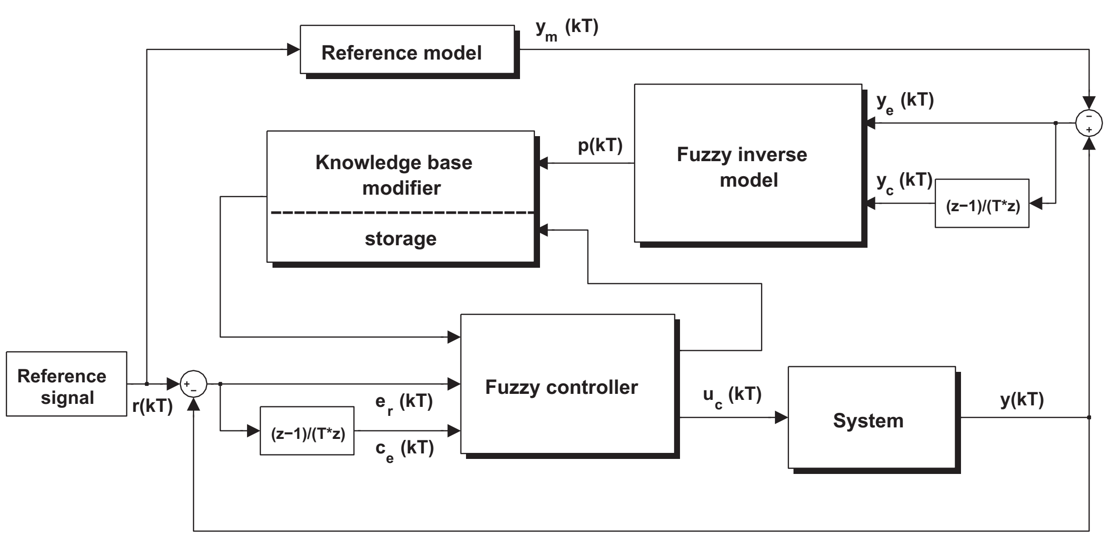

Fig. 1. Scheme of the FMRLC.