International Journal of
Intelligent Systems and
Applications in Engineering
ISSN:2147-6799 www.atscience.org/IJISAE
Advanced Technology and Science
Original Research Paper

Nonstationary Fuzzy Systems for Modelling and Control in Cyber Physical Systems under Uncertainty

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Accepted : 11/07/2017 Published: 31/07/2017

Abstract: The applications of cyber-physical systems (CPS), which have a wide range from industrial to medical, are increasing day by day thanks to its reliable, scalable and flexible structure. In a CPS, the consistency and reliability of system are much more important, because they are generally used in large-scale and critical tasks. Uncertainties are unexpected situations and no matter how well a system designed they are a threat to a system always. Fuzzy logic is one of the algorithms that can be utilized in cyber layer easily. But because of its insufficiency in handling uncertainties new fuzzy types are emerged. Nonstationary fuzzy system is a type of fuzzy logic which is able to handle uncertainty in reasonable time. In this study a new inference system for nonstationary fuzzy systems is developed to enhance nonstationary fuzzy systems. The system is based on two main steps, first adding some random uncertainties to nonstationary inputs, and second obtaining single output value for the inputs. Thus, the fuzzy system always has uncertainty and the behavior of system is prepared for the uncertainties. The proposed method is verified by simulation results which demonstrate the effectiveness of system especially for noisy data compared to the type-1, and nonstationary fuzzy systems. The proposed method can be used in CPS which need consistency and robustness.

Keywords: *cyber-physical systems, fuzzy logic, nonstationary fuzzy, uncertainty.*

1. Introduction

CPS has multi-layered structure whose cyber and physical components are in different layers, but tightly integrated thanks to communication technologies. Simple CPS system works as [1]:

1- Gathered data by sensors are sent to cyber layer with the help of communication technologies.

2-The data reached to cyber layer are used to calculate the state of system and produce the necessary commands.

3-The commands are transferred to physical components such as actuators thanks to communication technologies, and the system works in this loop (Fig. 1).

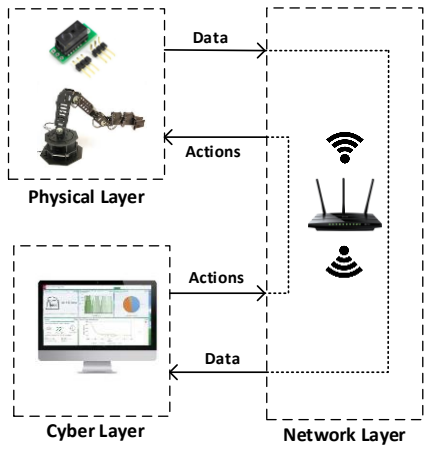


Fig. 1. The block diagram which shows simply how a CPS works [2].

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Note: This paper has been presented at the 5th International Conference on Advanced Technology & Sciences (ICAT'17) held in Istanbul (Turkey), May 09-12, 2017

CPS whose cyber and physical components are diverse, may have uncertainties due to cyber, physical or communication layer [3]. Robustness, reliability, safety, and security are main challenges to implement CPS [4]. As CPS are mission-critical system; ensuring safety, security, and sustainability of such systems is very important [5]. Fuzzy decision systems can be applied easily in CPS thanks to its layered structure. So, fuzzy systems which known by their success in handling uncertainty, are preferred in CPS applications [6]. A block diagram for CPS based field monitoring study is given by fig. 2 [7].

Fuzzy systems, which aims to emulate human decision mechanism, have been used in decision making problems for years. But because they are not capable to handle uncertainties much, it brings the need of enhanced versions of fuzzy logic. Specialized fuzzy system to handle uncertainty, which is called type-2 fuzzy

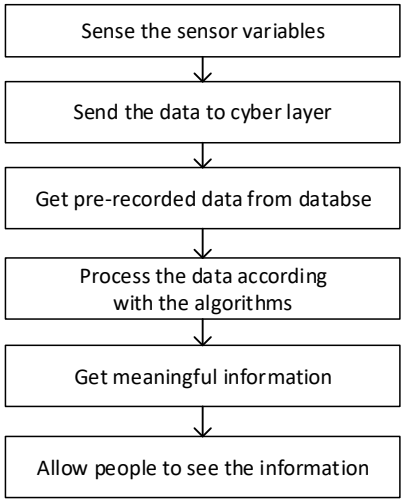


Fig. 2. Sample CPS for monitoring potato fields [7].

system, is developed. Furthermore, nonstationary fuzzy systems, which aims to model type-2 inputs with type-1 sets, are evolved to handle uncertainties in fuzzy systems with reducing the computational burden of type-2 sets [8].

Fuzzy systems have been subjected to researches since it is announced by Zadeh [9]. One of the studies which benefit from fuzzy logic is Esposito's study. Esposito et al. aim to select a suitable cloud storage service for customer's needs considering uncertainty in the expression of subjective preferences with the help of fuzzy logic [10]. Aladi et al. make a comparative study for type-1 and type-2 sets. They use type-2 fuzzy sets with different amount of footprint of uncertainty (FOU) size, and they demonstrate the effect of change in FOU on sets with different noise values [11]. Petrou et al. use Dempster–Shafer theory to habitat mapping, in combination with fuzzy logic. They report that using DS principles help them in enhancing classifier, and using fuzzification approaches help them in improving the results which are obtained by crisp classification [12]. Lochan et al. examine 65 papers about control of 2-DOF (degrees of freedom) robot manipulator in the literature. They highlight that using fuzzy logic rather than classical controller improve the robustness of the system considerably [13]. Gonzalez et al. propose an edge detection method based on the Sobel edge detection method with using generalized type-2 fuzzy logic systems. In order to reduce the complexity of general type-2 systems, they utilize the α-planes theory. Classical Sobel, type-1 fuzzy, interval type-2, and generalized type-2 system are compared to show advantages of method [14].

In this paper, nonstationary fuzzy sets are utilized both to avoid of complexity of general type-2 sets and to ensure the change in secondary memberships that interval type-2 sets are not capable. In order to enhance the results of nonstationary sets especially for uncertain status, random memberships are created within the FOU size. The memberships are combined according to the algorithm and the final crisp output obtained.

2. Nonstationary Fuzzy Systems

Nonstationary fuzzy sets are emerged from the idea of representing type-2 fuzzy sets with type-1 fuzzy sets in order to reduce the computational complexity of type-2 fuzzy sets. A nonstationary fuzzy system can be considered as collection of type-1 systems. So, in order to understand nonstationary fuzzy systems, type-1 and type-2 fuzzy systems should be comprehended first.

2.1. Type-1 and Type-2 Fuzzy Systems

Fuzzy systems are emerged from the need of emulating human decision mechanism. Fuzzy sets are suggested to prevent the disadvantages of sharp changes in classical set theory.

For example, while in classical set theory the input 176 may considered as short absolutely; the same input may be considered 0.7 tall, 0.3 short according to fuzzy set theory. Although it helps to give softer decisions for changes, uncertainties are still a problem for type-1 fuzzy sets. In order to handle uncertainties, type-2 fuzzy sets are developed.

Uncertainty means a situation in which something is not known. Uncertainties are known as unexpected situations which are occurred from instant mistakes of devices or insufficient examination of system. But different expert views may also, cause uncertainties. While one may say the membership of tallness is 0.7 for 176cm of input, another one may say 0.75 for the same input. No matter how it is occurred, the way to represent uncertainties is type-2 fuzzy sets. Type-2 fuzzy sets have two membership functions which are upper and lower membership function. A type-2 fuzzy set example and second membership function for input 176 is given by fig. 3.

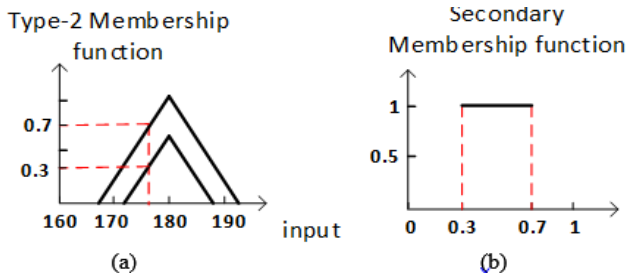


Fig. 3. Type-2 fuzzy (a), secondary membership function of 176 (b).

Secondary membership function may vary for different input values, so type-2 fuzzy systems have generally complex computational requirements. If the second membership function is constant for all inputs, like in fig. 3.b, then the type-2 set is called interval type-2 fuzzy set and it need less computational requirements than general type-2 systems. A comparative presentation of type-1, type-2 and interval type-2 sets is given by Fig. 4.

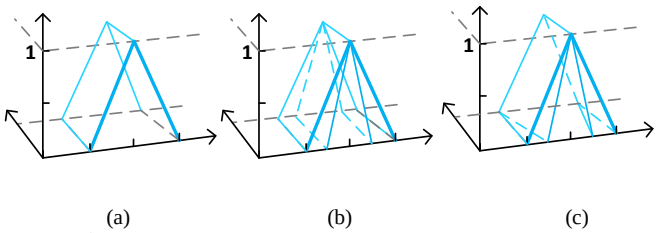


Fig. 4. T1 fuzzy set (a), interval T2 set (b), and general T2 set (c).

Classical type-1 fuzzy systems consist of fuzzification, inference, and defuzzification steps. In type-2 fuzzy systems there is one more step in addition to these steps which comes after inference system and is called type-reduction. A block diagram of type-1 and type-2 system steps are given by fig. 5.

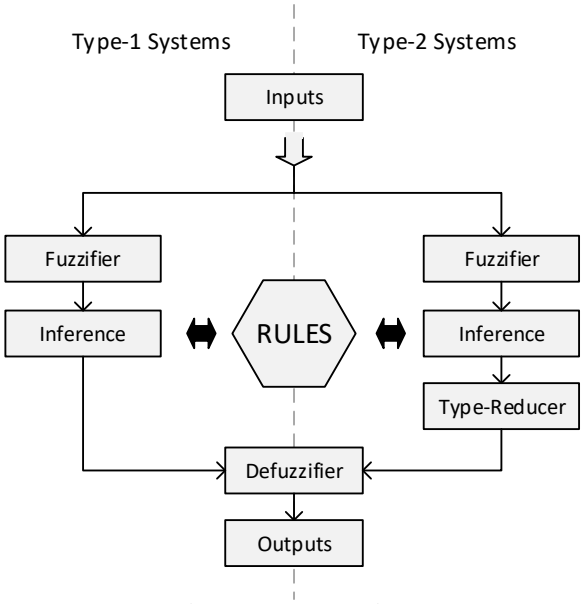


Fig. 5. A block diagram for type-1 and type-2 fuzzy system steps.

2.2. Nonstationary Fuzzy Systems

The complexity of interval type-2 fuzzy systems is lower than general type-2 fuzzy system's. But it is not appropriate to consider variety in time. So, nonstationary fuzzy systems are emerged to fill the gap with reducing the complexity of general type-2 fuzzy systems. Nonstationary fuzzy systems aim to model type-2 systems with using a collection of type-1 systems.

Nonstationary sets for representing type-2 sets, can be produced by two different approach mainly. One of them is change in width, another one is change in centre [15]. The example set created by change in centre is given by fig. 6.

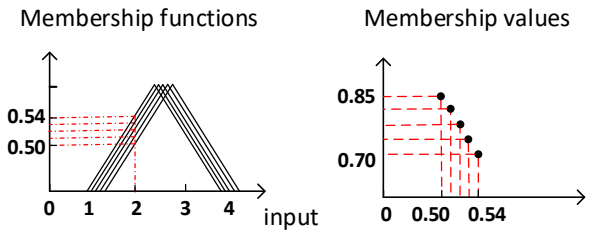


Fig. 6. Nonstationary sets (a), and memberships for input of 2 (b).

With the information given above, a nonstationary fuzzy system mechanism can be shown like in fig. 7. After employ type-1 fuzzy system n times, final de-fuzzifier, which aims to get final outputs from the set of results obtained by type-1 processes chain, is applied.

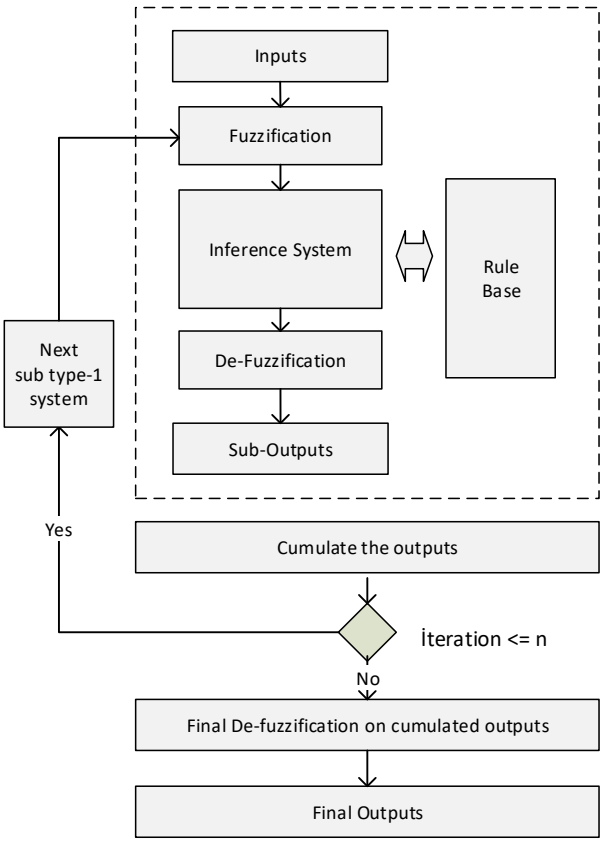


Fig. 7. Block diagram of nonstationary fuzzy system mechanism.

3. Proposed Approach

A system is vulnerable to uncertainties because a system is unexpected situation for systems. In this study, we aimed to make system familiar with uncertainties by adding randomly created inputs.

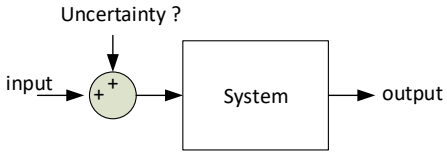


Fig. 8. Classical systems

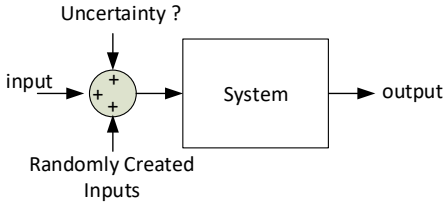


Fig. 8. Main idea of proposed method.

In figure 8, the system is waiting for robust data and any possible uncertainty in inputs will affect the system behavior badly. If the system is ready for uncertainty or randomness, like in fig. 9, any unexpected situation doesn't affect the system behavior much. In order to handle uncertainties in a system, the effect of possible uncertainties should be minimized. This is possible with making membership degrees softer. For example, classical set memberships have sharp transition and small changes on inputs may cause big differences. Fuzzy set membership functions have softer transition and small changes don't affect the system much as in classical set theory. In this study a method based on random memberships which near the original membership degree is implemented to minimize the effect of changes. The block diagram of proposed approach is given by fig. 9.

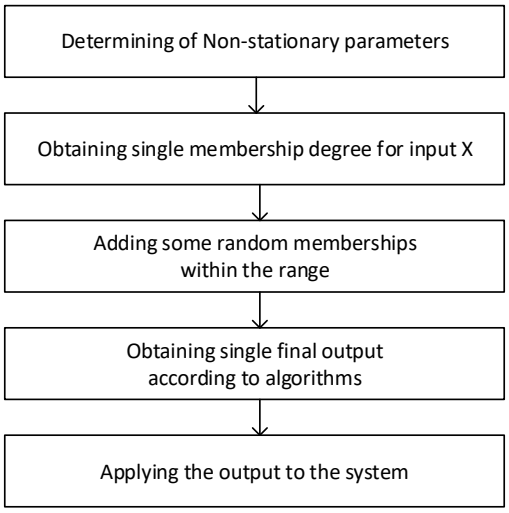


Fig. 9. Proposed approach.

Uncertainties are unexpected situations which all systems may have. In a CPS, uncertainties may occur from models in cyber layer, devices in physical layer or from communication layer. Uncertainties, both in general systems and fuzzy systems have a great deal of randomness, although they seem to be more systematic. It is possible to produce infinite number of random value in FOU area. But we limited the values in order to make available them for modelling. Triangular membership formulation and the formulation in order to produce random variables on it is

given by (1) and (2) respectively.

$$\max(\min\left(\frac{x-a}{b-a},\frac{c-x}{c-b}\right),0) \quad (1)$$

$$\min(\max\left(min\left(\frac{x-a}{b-a},\frac{c-x}{c-b}\right)+g.(R-R),0\right),1) \quad (2)$$

Where a is the left corner, b is the hill point, and c is the right corner of triangle; R are randomly created values by random number creators, and probably are not same values; g is weight whose value is the half of FOU size. The parameters are visualized for triangular function by fig. 10. For example, assuming that we take 4 random values in addition to the original membership rate and their weight like given in table 1. Then the new membership degree will be 0,4779 according to weighted average method.

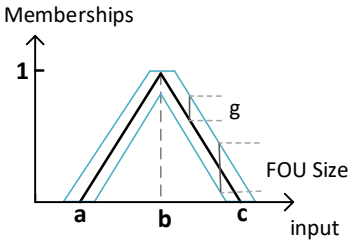


Fig. 10. The visualization of parameters of a,b,c,g, and FOU Size.

Table 2. Sample values for test

Value	Membership	Weight	Weighted Average
Random 1	0.3721	0.15	0.0558
Random 2	0.4432	0.15	0.0664
Random 3	0.4587	0.15	0.0688
Original	**0.5**	**0.4**	**0.2**
Random 4	0.5794	0.15	0.0869
			0.4779

In this way, it is aimed to minimize effect of possible uncertainty on a system with adding random memberships to original input memberships.

4. Simulation results

In order evaluate the performance of proposed method, DC motor position control problem is implemented in MATLAB. The block diagram for the system is given by fig. 11, and the transfer function for the system is given by (3).

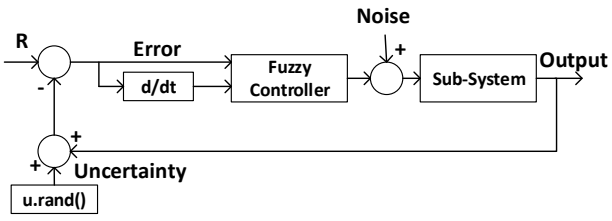


Fig. 11. The block diagram of proposed system

$$H(s)=\frac{2.2}{s(8.9\times10^{-6}s^2+7.2\times10^{-3}s+0.94)} \quad (3)$$

As seen by fig. 10, necessary inputs for modelling the effects of uncertainty and noise are added. In addition to proposed method, system is run with type-1 and nonstationary fuzzy systems. The fuzzy inputs and output for type-1 systems are given with rule base

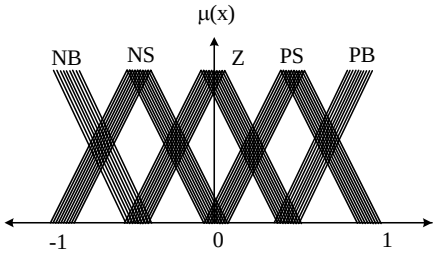


Fig. 12. Inputs and output membership functions.

	NB	NS	Z	PS	PB
NB	NB	NB	NB	NS	Z
NS	NB	NB	NS	ZE	PS
Z	NB	NS	Z	PS	PB
PS	NS	Z	PS	PB	PB
PB	Z	PS	PB	PB	PB

Fig. 13. Rules for DC motor control.

by fig. 12 and 13.

As seen by fig. 10, 5 linguistic variables which have triangular

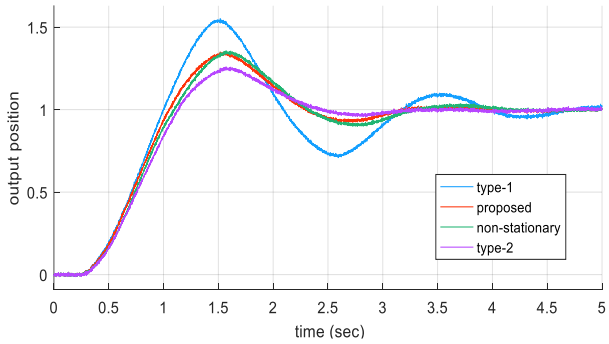


Fig. 14. Output positions for low noisy data.

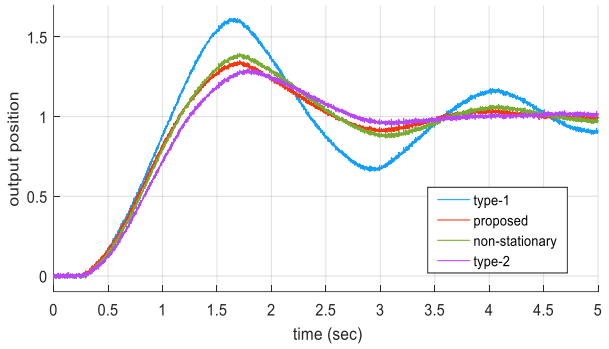


Fig. 15. Output positions for medium noisy data.

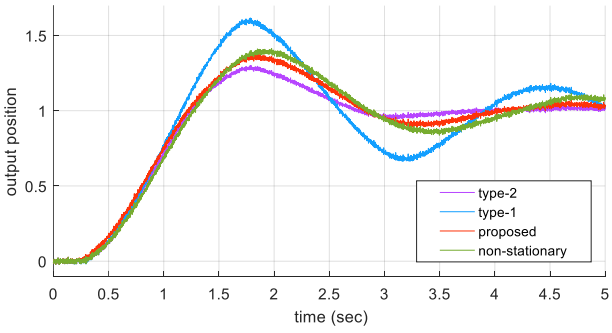


Fig. 16. Output positions for high noisy data.

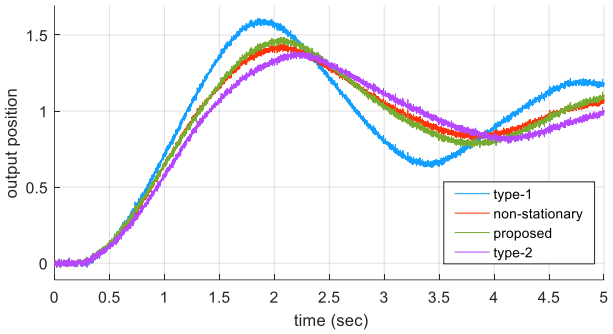


Fig. 17. Output positions for higher noisy data.

membership function are used. The inputs are made nonstationary with repeating 10 times in ±0.05 range uniformly. The memberships are normalized between [-1, 1] values. Min-max method is used for inference mechanism and centroid is used for defuzzification like in our previous study [17]. Fig. 14,15, 16 and 17 gives the comparative results belong to type-1, type-2, nonstationary, and proposed method. The noise rate that affects the system are selected as 5x, 7x, 9x, 11x respectively. Figures show us that type-1 inputs are poor in handling uncertainty. The results obtained by different simulations verify the effectiveness of system with comparative results.

5. Conclusion

Uncertainty is a big treat to CPS which are used in mission-critical tasks generally. The insufficiency in handling uncertainty is one of the biggest problem for fuzzy systems in CPS. Type-2 fuzzy system is developed to model uncertainties but its high computational needs make it unpractical. After, non-stationary fuzzy system, which provides better solutions then type-1 and needs less time than type-2 fuzzy systems, is introduced. With the knowledge of that the uncertainties are mainly due to random sources, in this study, it is suggested combining the randomly created memberships within the FOU size. This make the system always ready for uncertainties and possible uncertainties doesn't affect the system much. By adding the random membership to nonstationary fuzzy sets, uncertainties, which may have different impact value, can be modelled easily. The proposed approach is used to control the position of DC motor, and effective results are obtained. Simulation results for the proposed method are compared with type-1, type-2 and nonstationary systems. The results show us that bigger noise has a bigger bad effect on the system. The best coverage rate is obtained with type-2 controller, but the computational complexity of type-2 make proposed method ideal for use in real time CPS applications.

Acknowledgements

This work was supported by Scientific Research Projects Coordination Unit of Firat University. Project number: MF.17.09.

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