Overview of Type-2 **Fuzzy Logic Systems**

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ABSTRACT

Fuzzy set theory has been proposed as a means for modeling the vagueness in complex systems. Fuzzy systems usually employ type-1 fuzzy sets, representing uncertainty by numbers in the range [0, 1]. Despite commercial success of fuzzy logic, a type-1 fuzzy set (T1FS) does not capture uncertainty in its manifestations when it arises from vagueness in the shape of the membership function. Such uncertainties need to be depicted by fuzzy sets that have blur boundaries. The imprecise boundaries of a type-2 fuzzy set (T2FS) give rise to truth/membership values that are fuzzy sets in $\lceil 0 \rceil$, $\lceil 1 \rceil$, instead of a crisp number. Type-2 fuzzy logic systems (T2FLSs) offer opportunity to model levels of uncertainty which traditional fuzzy logic type I struggles. This extra dimension gives more degrees of freedom for better representation of uncertainty compared to type-1 fuzzy sets. A type-1 fuzzy logic system (TIFLSs) inference produces a TIFS and the result of defuzzification of the TIFS, a crisp number, whereas a T2FLS inference produces a type-2 fuzzy set, its type-reduced fuzzy set which is a T1FS and the defuzzification of the type-I fuzzy set. The type-reduced fuzzy set output gives decision-making flexibilities. Thus, FLSs using T2FS provide the capability of handling a higher level of uncertainty and provide a number of missing components that have held back successful deployment of fuzzy systems in decision making.

Keywords:

Applications of Type-2 Fuzzy Logic, Embedded Type-1, Embedded Type-2 Fuzzy Sets, Interval Type-2 Fuzzy Sets (It2fss), Type-1 Fuzzy Logic Systems, Type-2 Fuzzy Logic Systems, Type-2 Fuzzy Sets, Type Reduction, Uncertainty

INTRODUCTION

Type-1 fuzzy logic was first introduced by Zadeh (1965). Fuzzy logic systems are based on type-1 fuzzy set (T1FS) and have demonstrated their ability in many applications, especially for the control of complex nonlinear systems that are difficult to model analytically (Zadeh, 1973; King & Mamdani, 1977). Type-1 fuzzy logic systems (T1FSs) utilize crisp and precise type-1 fuzzy sets and thus the T1FSs

DOI: 10.4018/ijfsa.2012100101

can be used to model the user behavior under specific conditions (Zadeh, 1975a, 1975b). Type-1 fuzzy sets handle uncertainties by using precise membership functions that the user believes capture the uncertainties (Zadeh, 2005; Klir & Folger, 1988; Mendel, 2001; Mendel & Wu, 2002; Castillo & Melin, 2008). Once the type-1 membership functions have been chosen, all the uncertainty disappears, because type-1 membership functions are totally precise. The concept of a type-2 fuzzy set was introduced by Zadeh as an extension of the concept of an ordinary fuzzy set i.e., a type-1 fuzzy set (Zadeh, 1975b). All fuzzy sets are characterized by

membership functions. Type-1 fuzzy sets are characterized by two-dimensional membership functions in which each element of the type-1 fuzzy set has a membership grade that is a crisp number in [0, 1].

Type-2 fuzzy sets are characterized by fuzzy membership functions that are threedimensional. The membership grade for each element of a type-2 fuzzy set is a fuzzy set in [0, 1]. The additional third dimension provides additional degrees of freedom to capture more information about the represented term. Type-2 fuzzy sets are useful in circumstances where it is difficult to determine the exact membership function for a fuzzy set, which is useful for incorporating uncertainties (Mendel, 2001). Type-1 fuzzy sets are not able to directly model such uncertainties because their membership functions are totally crisp. On the other hand, type-2 fuzzy sets are able to model such uncertainties because their membership functions are themselves fuzzy (Coupland & John, 2008). And, if there is no uncertainty, then a type-2 fuzzy set reduces to a type-1 fuzzy set, which is analogous to probability reducing to determinism when unpredictability vanishes. Type-2 FLSs are applicable when (Mendel, 2001):

- The data-generating system is known to be time-varying but the mathematical description of the time-variability is unknown (e.g., as in mobile communications).
- Measurement noise is nonstationary and the mathematical description of the nonstationarity is unknown (e.g., as in a time-varying SNR).
- Features in a pattern recognition application have statistical attributes that are nonstationary and the mathematical descriptions of the nonstationarities are unknown.
- Knowledge is mined from a group of experts using questionnaires that involve uncertain words.
- Linguistic terms are used that have a nonmeasurable domain.

Rule-based type-2 FLSs can be applied to every area where type-1 rule-based. FLSs have been applied in which some uncertainty is present. Type-2 fuzzy sets can also be applied to non-rule-based applications of fuzzy sets, again if uncertainty is present. The uncertainty is the imperfection of knowledge about the natural process or natural state. The statistical uncertainty is the randomness or error that comes from different sources as we use it in a statistical methodology. There are different sources of uncertainty in the evaluation and calculus process. The five types of uncertainty that emerge from the imprecise knowledge natural state are (Mendel, 2001):

- Measurement uncertainty. It is the error on observed quantities.
- Process uncertainty. It is the dynamic randomness.
- Model uncertainty. It is the wrong specification of the model structure.
- Estimate uncertainty. It is the one that can appear from any of the previous uncertainties or a combination of them, and it is called inexactness and imprecision.
- Implementation uncertainty. It is the consequence of the variability that results from sorting politics, i.e., incapacity to reach the exact strategic objective.

TYPE-2 FUZZY SETS AND OPERATIONS

Type-2 sets can be used to convey the uncertainties in membership functions of type-1 sets, due to the dependence of the membership functions on available linguistic and numerical information (Mendel, 2001). The clear definitions of type-2 fuzzy set have been discussed in previous studies (Mendel & Liu, 2009; Castillo & Melin, 2008; Mendel, 2003, 2007a, 2007b; Mendel & John, 2002; Tuksen, 2002; Karnik & Mendel, 2001a, 2001b; Karnik & Mendel, 1998; John, 1998a, 1998b; John & Czarnecki, 1999). Moreover, John and Czarnecki (1999) have pointed out that "The useful-

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