Fuzzy Estimation of Liver Stiffness in Modelling Liver Deformation

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***Abstract*—The skill of a successful operation requires a thorough understanding on the particular organs, perhaps de facto surgery is complex nowadays. Therefore, surgical simulator has become an alternative demanding tool among the surgeons to practice and conducting pre-operation planning. Due to the ease of implementation of Mass Spring Model (MSM), the context of MSM has been extended to real-time invasive surgical simulator. However, the remaining drawback of MSM is the selection of parameter—stiffness. In this research, the fuzzy knowledge based system is introduced into the MSM. We present an improved MSM to simulate the liver deformation for surgery simulation. The underlying MSM is redesigned where the parameters are determined by using knowledge-based fuzzy logic. Comparison between different fuzzy approaches such as Interval Type-2 Fuzzy Sets (IT2), Mamdani and Sugeno are made. Among the three fuzzy approaches, IT2 has the highest similarity with the benchmark model. The stiffness values estimated by fuzzy approaches are in very good agreement with the benchmark result as each of the respective fuzzy approach graphs share the similar trend of displacement and velocity with the benchmark model.**

Keywords— biomedical data modelling, knowledge utilization, spring parameters, mass spring model, interval type-2 FIS, mamdani FIS, sugeno FIS

I. INTRODUCTION

The skill of a successful operation requires a thorough understanding on the particular organs, including conditions and vessel distribution. Perhaps de facto surgery is complex nowadays, thus for a novice surgeon to practice on real patient is highly endangered. Therefore, surgical simulator has become an alternative demanding tool which offers strategies to reduce medical errors by learning and conducting pre-operation planning in virtual environment. However, the uniqueness of different patients, promote difference physical behaviours in soft tissue deformation. Hence, the selection of deformable model is essential as it is the core part of a surgical simulator. In order to design a state-of-the-art surgical simulator, one has to achieve both realistic and real-time simulation.

The Mass Spring Model (MSM) is the most commonly used deformable model. MSM is a discrete model which avoids initialization. It features high refreshing frame rates, which increase the efficiency. Therefore, MSM is more convenient in manipulating a deformable object in terms of real-time. The only remaining challenge of the MSM is the selection of parameters [19]. The determination parameters of MSM need improvement because the imprecise selection of spring parameters might cause tendency in the realism of deformation. The determination of spring parameter is strenuous as the parameters do not have direct relationship with the elastic constants-Young's Modulus and Poisson's ratio [4]. In the work of Besozzi et al. [4], suggested that spring constants are dependent on surgeons' prior knowledge.

In this research, the fuzzy knowledge based system is introduced into the MSM. We present an improved MSM to simulate the liver deformation for surgery simulation. The underlying MSM is redesigned where the parameters are determined by using knowledge-based fuzzy logic. The surgeon's prior knowledge and clinical data obtained from FibroScan® are the sources to be implemented in the system. Comparison between different fuzzy approaches such as Interval Type-2 Fuzzy Sets (IT2 FS), Mamdani and Sugeno are made. We investigated the respective suitability in terms of accuracy by examining the graph similarity of the respective fuzzy approaches with the benchmark model abstracted from Basafa and Farahmand [3].

II. PREVIOUS WORKS

The first surgical simulator was introduced by Robert Mann in the 60', where a rehabilitation application was developed to allow the medical surgeon to perform several surgical approaches for a given orthopaedic problem [10]. However, throughout the years, there is a remaining challenge in designing a state-of-the-art surgical simulator; as the ability to obtain both realistic and real-time simulation is a very difficult task. This is because the kernel portion of the surgical simulator—deformable model, by itself, the computational time is opposed to its operation.

Aforementioned, MSM is highly efficient, but inaccurate due to the selection of spring parameters. Thus, several

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approaches have been done in recent development in order to increase the accuracy of the simulation. In the past research, MSM has existed for more than two decades across multiple applications. For instance, cloth simulation [15,16], hair simulation [2], deformation of gallbladder [7] and soft tissue deformation [6]. Results from these research show efficiency in real-time interactive speed yet the accuracy and realism are doubted due to the selection of parameters [10,21,23].

The improvement of the conventional MSM could be broke into two branches: mathematical model [1,13,18,22] and optimization methods [5,6,8]. These approaches have shown significant improvement in terms of computation efficiency. However realism remains an issue. This is because most of the proposed models are limited to certain mesh topologies. Moreover, the specifications of spring constraints are not straightforward. Thus, there is an urge to improve the determination of MSM in order to simulation the soft tissue deformation realistically.

Concurrently, fuzzy approaches have been widely expanded and several fuzzy control strategies have been developed based on different classical control methods, such as PID-fuzzy control [9], modelling of stress-strain relationship of concrete in compression [17], sliding-mode fuzzy control [21], neural fuzzy control, adaptor fuzzy control [11] and phase-plan mapping fuzzy control [12]. The uncertainty which exists in fuzzy logic allows the system to cope with imperfect input and adapt as the situation changes. The fuzzy algorithm "inform" the machine how to control the system instead of learning by observing the actions of a human operator. The main recipe in fuzzy approaches is the availability of knowledge which consists of a specific domain being a field or area of expertise. Therefore, the generally well-structured domain could reduce the complication of calculations. For instance, the work of Pawlus et al. [14], shows that the fuzzy model's output could be adjusted to improve the model's fidelity without complicated calculations. We thus could implement the fuzzy approaches into MSM in order to sort the selection of parameters based on the available liver stiffness data obtained from FibroScan®.

III. Methodology

In this study, the Fuzzy Logic Toolbox and Generalized Fuzzy System (GFS) are implemented in MATLAB r2014a to model the Fuzzy Inference System (FIS). Three types of fuzzy approaches are designed to obtain the stiffness coefficient of the Mass Spring Model. The GFS is an open source toolbox which is developed for visualizing fuzzification using all types of fuzzy sets. It could be reached at http://sourceforge.net/projects/gfs. The liver data are obtained from http://gforge.inria.fr/frs/?group_id=690.

A. Mass Spring Model (MSM)

The human liver 3D modelling is based on the MSM. The liver is modelled as a collection of mass points linked by three different springs such as structural spring, shear spring and flexion spring.

The springs linking each mass points exert forces on neighbouring points when a mass point is displaced from its rest position. The governed MSM equation is derived by using Newton's 2nd Law of Motion, F_N and Hooke's Law.

However, in actuality human liver deformation, there exists some degree of damped deformation caused by friction forces. Thus, we assume that the mass spring modelling is a damped harmonic oscillation and the damping coefficient, γ is taken account in the governing MSM equation as follows:

$$m\ddot{x}_{ijk}(t) + \gamma \cdot \dot{x}_{ijk}(t) + k \cdot x_{ijk}(t) = F_{ext} \tag{1}$$

where m , γ and k are the mass, damping coefficient and stiffness coefficient, respectively. While $\ddot{x}_{ijk}$, $\dot{x}_{ijk}$ and x_{ijk} denote the acceleration, velocity and displacement of a control mass point in 3D space. F_{ext} represent the external forces.

There are two major properties in determining the MSM parameters for each of the springs: stiffness coefficient (k) and the damping coefficient (γ). The stiffness constant is the resistance of a deformable object when a force is applied along a given degree of freedom and a set of loading points and boundary conditions are prescribed to the deformable object. In this paper, the stiffness coefficient will be determined in Fuzzy Inference System (FIS) by implementing the available knowledge and data from previous medical research. The detailed determination of stiffness coefficient by using the FIS will be further discussed in next section.

Damping constant, on the other hand, is the capacity built into a biomechanical or electrical device to prevent excessive correction and the resulting instability or oscillatory conditions. The derivation of damping coefficient is directly related to the damping ratio and natural frequency. Assume that the deformation of human liver is a damped harmonic oscillation, we could obtain the damping constant by applying (2) as follows:

$$\gamma = \frac{2\varsigma k}{w} \tag{2}$$

where γ , ς , k and w denote the damping constant, damping ratio, stiffness coefficient and natural frequency, respectively. Aforementioned, the behavior of the system depends relatively on the natural frequency, w and the damping ratio, ς . Knowing that when $\varsigma \to 0$, the system is basically in undamped condition. Meanwhile, when $\varsigma < 1$, the system is underdamped in which the friction force is directly proportional to the velocity of the object. When $\varsigma > 1$ or $\varsigma = 1$, the system would be overdamped or critically damped in which the system return to equilibrium without any oscillation.

In this paper, we assumed that the human liver deformation is an underdamped system, thus the damping ratio is set to be 0.9. This is because when $\varsigma < 0.9$, the resulting damping constant does not fulfil the value in the range of benchmark damping constant as shown in Table 1. Apart from that, based on the resulting dependency of damping ratio, we could not set $\varsigma = 1$ *or* > 1 as it will cause the system to become critically damped.

B. *Fuzzy Inference System (FIS)*

Generally, a fuzzy inference system (FIS) is built up by three components—rules, database and reasoning mechanism. The rules consist of a collection of available linguistic knowledge. Whereas the database consist of a bunch of crisp sets which defines the membership functions based on the rules. Here, the database are made up of the sources obtained from the past research based on FibroScan®. The reasoning mechanism performs fuzzy decision making upon the rules and given facts to derive the outputs. In FIS, the inputs could either be fuzzy or crisp (exact value) inputs, however, the output shall always be crisp value in order to be implemented into the real-world system.

Mathematically, assume that we have two crisp sets (inputs), A and B where A is a crisp set of x, denoted as $\mu_A(x)$ and B is a crisp set of y, denoted as $\mu_B(y)$. Then, by applying the IF-THEN knowledge-based rule as a decision making mechanism, such that

If x is A and y is B then z is C. We have, the two-input single-output FIS with the intersection (AND) relationship between crisp sets A and B as follows:

$$
\begin{aligned}
&R_z(x, y) : A(x) \cap B(y) \rightarrow C(z) \\
&\therefore \mu_{R_Z}(x, y) = f(\mu_A(x), \mu_B(y))
\end{aligned} \tag{3}
$$

Next, the crisp sets is fuzzified by three different fuzzy approaches. Thus, we have the following minimum operator such that

$$
R = A \cap B = \min[\mu_A(x), \mu_B(y)], x \in X, y \in Y \tag{4}
$$

C. *Reasoning Knowledge to Rules*

In this study, the data sets used as knowledge-based rule are obtained from previous medical research. According to the medical literature review, the corresponding values of stiffness coefficient are obtained by using FibroScan® or Magnetic Resonance Elastography (MRE) techniques. Both of these techniques are considered as accurate and non-invasive.

Here, by using (4), the rules matrix as shown in Table I is built. Notice that, in Table I, if there exists "AND" intersection between the inputs $\mu_A(x)$ and $\mu_B(y)$, it is denoted as 1, otherwise. After the rule matrix of the corresponding inputs has been built, we proceed to the reasoning of knowledge into rules by using the Fuzzy Logic Toolbox and the Generalized Fuzzy System (GFS) in MATLAB r2014a.

TABLE I. THE "AND" INTERSECTION BETWEEN THE INPUTS

INPUTS	HCV	HBV	ALD	CLD	NAFLD
HCV	1	0	0	0	0
HBV	1	1	0	0	0
ALD	1	1	1	0	0
CLD	1	1	1	1	0
NAFLD	1	1	1	1	1
B - C	0	0	0	0	0
A – C	0	1	0	0	0
L – C	0	1	1	0	0
N – C	0	1	1	1	1
A – B	0	0	0	0	1
L – B	0	0	1	0	1
N – B	0	0	0	1	0
A–C–B	0	0	0	0	0
L–C–B	0	0	1	0	0
N–C–B	0	0	1	1	0

D. *Construction of Mamdani Fuzzy Inference System (M_FIS)*

The Mamdani FIS is constructed through MATLAB r2014a Fuzzy Logic Toolbox as shown in Fig. 1. It consists of Fuzzy Inference System (FIS) editor, Membership Function Editor, Rule Editor, Surface Viewer and Rule Viewer. In this study, Gaussian function (gaussmf) is used to represent the membership functions for each of the inputs. While Centre of Gravity (COG) defuzzification method are implemented to obtain crisp output.

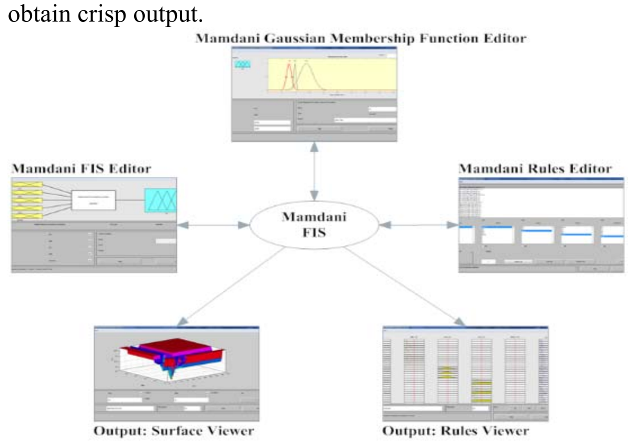

Figure I. Mamdani FIS with Gaussian Membership Functions

E. *Construction of Sugeno Fuzzy Inference System (S_FIS)*

In this study, the Sugeno FIS is directly transformed from Mamdani FIS by implementing MATLAB r2014a function—*mam2sug*. The output membership functions of the returned Sugeno system are constants produced from the centroids of the consequent membership functions of the original Mamdani FIS. The antecedent remains unchanged. The syntax of implementing the mam2sug is illustrated as follows:

mam_fismat = readfis('M_FIS.fis');
sug_fismat = mam2sug(mam_fis);

After the sug_fismat is generated in the MATLAB workspace, we then import it to the Fuzzy Logic Toolbox. The outcomes of the Sugeno FIS is shown in Fig. 2.

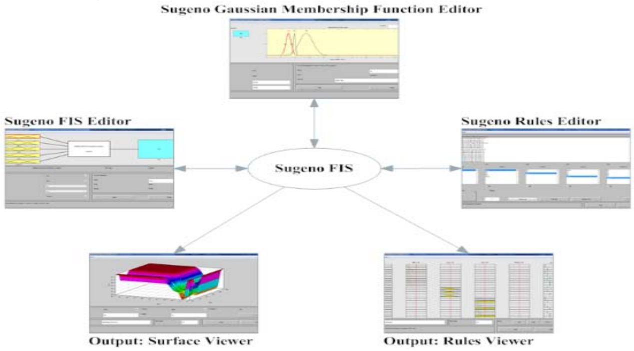

Figure II. Sugeno FIS with Gaussian Membership Functions

F. *Construction of Interval Type-2 Fuzzy Inference System (IT2_FIS)*

The interval type-2 FIS is constructed by implementing the open source Generalized Fuzzy System (GFS) into MATLAB. The GUI of GFS is similar to the MATLAB Fuzzy Logic Toolbox. To start the GFS, we first have to change our working directory in MATLAB environment to the folder we unzipped the GFS, says C:\GFS. Then, type 'FUZ' in the command window and press 'Enter'. A GUI for GFS will be opened as shown in Fig. 3. The rules can simply be added to the IT2 FIS by appending the existing rules from M_FIS or S_FIS to the generated IT2 FIS MATLAB script. The membership functions of this approach is different with the first two FISs. The shaded region is known as the Footprint of uncertainty (FOU). This region is the interval of uncertainty. The more area in the FOU simply means the more is the uncertainty.

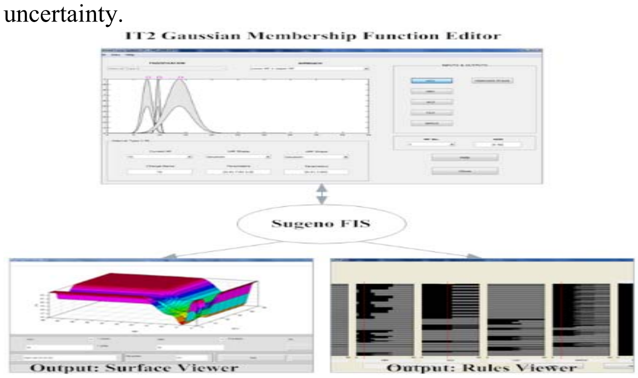

Figure III. Interval Type-2 FIS with Gaussian MFs.

G. *Benchmark Model*

In this paper, the benchmark model is abstracted from Basafa and Farahmand (2011). Basafa has developed an improved Mass Spring Damper model to simulate the nonlinear viscoelastic behaviour of the biological soft tissues which interact with a surgical indenter. The model can be further extended to exhibit viscoelastic behaviour by adding the damping force which reacts directly to the mass point proportionally to the velocities, parallel to the spring.

The general equation is similar to (1) such that

$$M_i \ddot{r}_i + b_0 \dot{r}_i + b_1 \left\| r_i - r_1^0 \right\| \dot{r}_i + \sum_{j=1}^{N} F_{ij}^s \frac{r_i - r_j}{\left\| r_i - r_j \right\|} = F_i^{ext} \tag{5}$$

In the benchmark model, F_i^s is used to demonstrate a highly non-linear elastiv behaviour of the soft tissue. The function F_i^s is expressed in a two-step expression of the force-displacement characteristics, in the form of a third degree polynomial at low displacements, and a linear behaviour at higher displacements, such that

$$F_i^s(X) = \begin{cases} K_1 X + K_2 X_C^3, & \left| X \le X_C \right| \\ (A + B(|X| - |X_C)) \left| \dfrac{X}{|X|} \right|, & \left| X > X_C \right| \end{cases} \tag{6}$$

where K_1 and K_2 are constants, X_C is the critical displacement of the nonlinear springs and parameters A and B are defined as follows:

$$A = K_1 X + K_2 X_C^3$$
$$B = K_1 + 3K_2 X_C^2, \tag{7}$$

Thus, the stiffness coefficient of the spring is

$$F_s = F_{ijk}(X) \left[\frac{\vec{x}_{ijk}}{\left| \vec{x}_{ijk} \right|} \right]_0^1 \tag{8}$$

with $x_{ijk} = x_1(X) - x_0(X)$

Next, to achieve more realistic viscoelastic behaviour of the soft tissue deformation the nodal damping forces are further extended in the benchmark model. A displacement-velocity component and the typical velocity alone component are assumed to exist in the damping force. Thus, F_i^d is expressed as follows:

$$F_d = \gamma_0 \dot{x}_i + \gamma_1 \left\| x_i - x_i^0 \right\| \dot{x}_i = \dot{x}\left(\gamma_0 + \gamma_1 \left\| x_i - x_i^0 \right\| \right) \tag{9}$$

where γ_0 and γ_1 are two damping constants. x_i and x_i^0 are the position vector and initial position of node i, respectively. The corresponding parameters of this benchmark model are tabulated as below:

TABLE II. THE BENCHMARK PARAMETERS

Parameters	Value
K_1	0.05 N
K_2	10 N
X_c	0.2
γ_0	2 Ns/m
γ_1	1000 Ns/m^2

However, there remains a major issue in the benchmark model which is the determination of model parameters

K_1 , K_2 , X_C , γ_0 and γ_1 . Although the parameters are somehow related to the soft tissue mechanical properties, the relationship is not well defined. Therefore, these parameters do not directly determine with specific constraints. The parameters are often tuned manually by fitting the experimental data into the model.

IV. FINDINGS

A. Results

In this paper, there consists of 247 rules which are generated based on the rule matrix as shown in Table I with the corresponding membership functions for each of the inputs. The output intersection in terms of surface plot and pseudo-color for each of the fuzzy approaches are shown in Fig. 4. Meanwhile, Fig. 5 illustrated the outcome of the comparison between the benchmark model and fuzzy approaches in terms of displacement vs time, velocity vs time and velocity vs displacement (phase plane plot).

B. Discussion

As shown in Fig. 4, the surface plot and pseudo-color of the IT2 FIS allows more intersection compared to the Mamdani FIS and Sugeno FIS. This is because IT2 consists of type-2 membership function with certain level of uncertainty interval while the membership functions for the other two are made up of crisp sets. In Fig.5, it showed that the graphs between the IT2 FIS, Mamdani FIS and Sugeno FIS with the benchmark model seems to share the similar trend. Therefore, the fuzzy approaches in this study show that the stiffness value predicted by FIS are in very good agreement with the benchmark result. However, how accurate is the stiffness value between three of these fuzzy approaches?

In order to answer this research question, it is crucial to obtain the graphs similarity between each of the fuzzy approach graphs with the benchmark graph. Taking each of the graph vertices, the graphs similarity is measured. The range of similarity is [0 1]. The closer the fuzzy approaches graph similarity value to 1, the more similar it would be with the benchmark graph. Each of the graphs similarity are shown in Table III, notice that among the three fuzzy approaches, IT2 has the highest similarity with the benchmark model. Thus, the stiffness value obtained from IT2 is the most accurate among the three.

TABLE III. GRAPHS SIMILARITY

Graphs		**Similarity [0 1]**
Benchmark	IT2	0.8598
Benchmark	Mamdani	0.8580
Benchmark	Sugeno	0.8549

V. CONCLUSIONS

In this study, the fuzzy approaches are proved to be powerful approaches in building complex and nonlinear relationship between a set of input and output data. The stiffness values estimated by fuzzy approaches are in very good agreement with the benchmark result. The corresponding graphs for each of the fuzzy approaches share the similar trend of displacement and velocity with the benchmark model. Among three of the fuzzy approaches, the Interval Type-2 FIS has the highest similarity with the benchmark model.

For future development, the Interval Type-2 FIS shall be improved in terms of real-time efficiency. More professional knowledge shall be added to further improve the accuracy of the fuzzy inference system.

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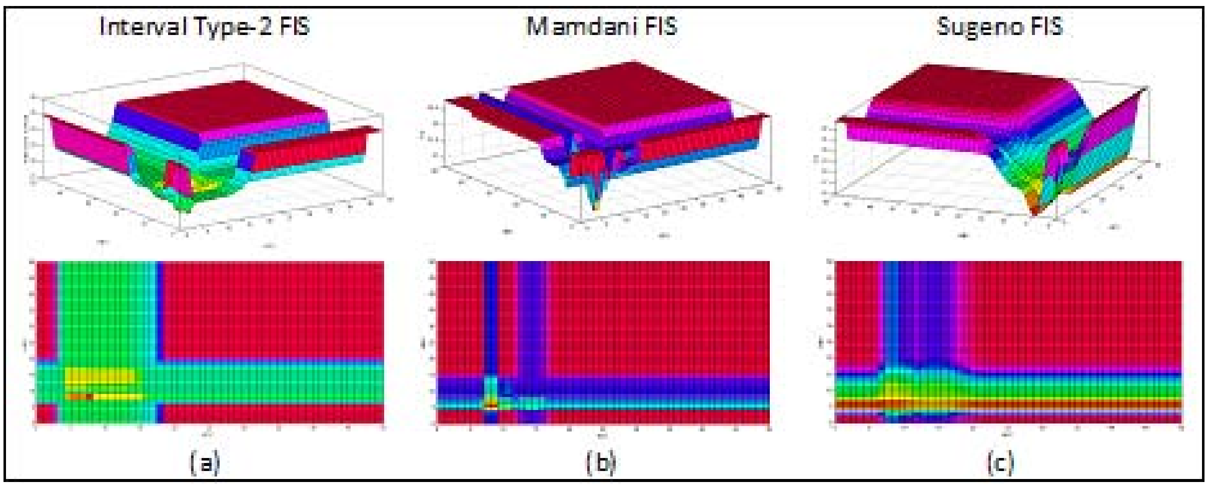

Figure IV. Surface view of Three Different Approaches

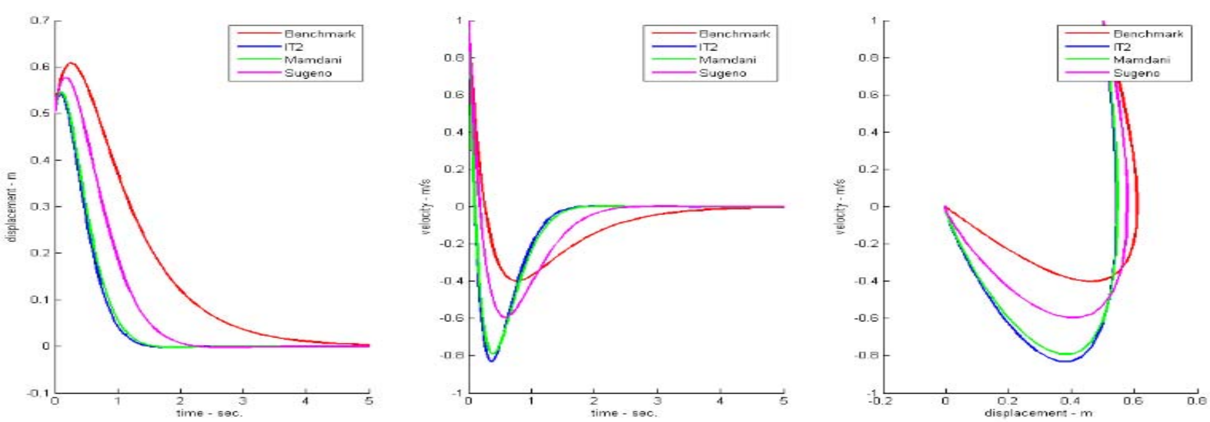

Figure V. Comparison between the benchmark model and fuzzy approaches.