Interactive Extraction of Featuresin 3D Flow with Fuzzy Theory

Enya Shen, Huaxun Xu, Wenke Wang, Xun Cai, Liang Zeng and Sikun Li

School of Computer, National University of Defense Technology, Changsha 410073, China

Abstract—Feature visualization plays an important role in visualization of complicated flows because it can highlight the feature of the flows with a simplified representation. The traditional feature visualization methods may exact some important features in flow field imprecisely due to the lack of the knowledge and the experience of the user. This paper gives a particle-based visualization system which is developed with the application of the interactive fuzzy feature extraction and interactive visual analysis theories. To obtain a more precise feature extraction, we have proposed an interactive fuzzy feature description language (FFDL) and an interactive fuzzy feature extraction algorithm. Based on the work before, we introduced the proportion ration for different rules and optimized our algorithm in practice further by communicating with specific researchers and doing lots of experiments. The further experiments show that our method can not only make full use of the ability of the user to extract the features precisely, but also reflect the uncertainty of the numerical simulation data.

Index Terms—Interactive Fuzzy Feature Extraction; Fuzzy Feature Description Language; Human-Computer Interaction; Interactive Visual Analysis;

I. INTRODUCTION

Feature visualization, which is very useful in Computational Fluid Dynamics (CFD), is dealing with larger data with the development of simulation technology and high performance computation. Moreover, there datasets contain more complicated features, which introduce a new challenge to 3D flow visualization. Feature visualization techniques extract and visualize the feature(s) of interest (FOI) for users. Due to the ability to clearly and efficiently extract and visualize the main features in the large data, feature visualization has become one of the most important visualization methods used by related researchers to analyze complex flow field computational models and physic laws.

3D flow feature visualization mainly contains feature description, extraction, rendering etc. In order to combine the visualization with special researchers' knowledge and experience, interactive visualization should be employed in the feature visualization systems.

The popular CFD visualization systems, such as Tecplot and EnSight, mainly use automatic feature extraction algorithm.

Manuscript Received on May 10, 2011 Email: shenenya.nudt@gmail.com However, these algorithms cannot extract flow features precisely due to the following two reasons. On one hand, there are no unified and strict definitions of some important flow features, such as vortex in CFD. The existing algorithms usually use experiential formulas, which reduce the precision of the results and limit the range of the application. On the other hand, there is some uncertainty in the flow data due to the computation methods and computer precision, which is not taken into account by the traditional feature extraction algorithms. Burger et al. [1] took several traditional vortex extraction methods into one framework, with which users can choose more practical methods in different situations. In order to visualize the uncertainty of the result of the vortex extraction method, transparency code and direct volume rendering were used to visualize the selected region. Doleisch and Gasser [2] proposed a simple Feature Description Language (FDL) and realized a variety of interaction methods to develop a useful interactive visualization system SimVis. Although the proposed logic operations in FDL can deal with the complicated flow features, it cannot illustrate the importance degree of the feature attribute and the features membership.

Just as Chris Johnson said [3], "Visualization scientists need to spend more time understanding the underlying science, engineering, and medical applications." This paper optimizes our algorithm in practice further by following instructions by Chris Johnson:

- Observe and describe the FOI, communicate with CFD researchers. And we get why several feature extraction algorithms are not good at various application problems as said before. On the other hand, we got the idea to combine these traditional algorithms reasonably and made use of fuzzy theory to cope with the uncertainty in datasets. We also learned from there researchers that it is very important to develop an interactive algorithm to let them communicate with their datasets, The 1987 National Science Foundation Visualization in Scientific Computing workshop report said, "They want to interact with their data" [4].
- Formulate a hypothesis; we will discuss our optimized formulations in Section 2 briefly, see [5] in detail.
- Use the hypothesis to look into FOI in the datasets; we will discuss what we got by our algorithm in Section 3 in details.

We also give a particle-based visualization system which is developed with the application of the interactive fuzzy feature extraction algorithm [5]. The further experiment results dem-

onstrated that the proposed feature extraction algorithm is accurate, effective and practical.

II. OPTIMIZED FFDL

2.1 Optimized FFDL

The features of 3D Flow Field have two meanings [6]: (1) The shapes, structures and phenomenon of the meaningful physical cases (such as vortex, turbulence, and shock surface) in vector field, and (2) The interested regions extracted from the data field. The structure of 3D flow field is always complex, hard to be defined and described precisely. Fuzzy theory, which has strong description ability, is very important for the understanding of the complex phenomenon.

However, we found that every feature extraction algorithm has its own advantages in practice, and it is needed to denote how important an algorithm is in various combinations of there algorithms. That's to say, to realize a widely useful framework, it is important to distinguish every extract rule's proportion in different scene. So we introduce a variety, ProportionRation, to denote the importance degree of the extract rules.

To optimize our algorithm FFDL for practical use, we integrate FFDL with ProportionRation. Fig. 1 shows the optimized model for FFDL, Here we introduce this model briefly. Please see [5] in detail.

The attributes of flow field can be classified into three categories: basic attributes Φ , derived attributes Υ and associated attributes Π . Basic attributes Φ which describe the basic space and orientation information include space variable $x \in \mathbf{R}^3$ (\mathbf{R}^3 is 3D coordinate system) and velocity vector \mathbf{V} . Derived attributes Υ are attributes calculated from existing attributes, such as vortex magnitude, velocity gradient tensor. [2] lists common derived attributes. And associated attributes Π is the attributes other than basic attributes and derived attributes in the data, such as temperature, pressure and density. Considering the fuzziness of the attributes, we introduce flow definitions with fuzzy theory:

Definition 1: Flow Feature (FF): For flow field $U(\Phi, \Upsilon, \Pi)$, one flow feature with any attribute (i) is a fuzzy set. So,

$$F' = \left\{ x, \mu_F' \left(U(x) \right) \right\}, \quad x \in \mathbf{R}^3$$

$$\mu_F' \left(U(x) \right) = \mu_F' \left(\Phi(x), \Upsilon(x), \Pi(x) \right) \in [0, 1]$$
(1)

Where membership function μ'_F defines a map from U to [0,1], $\mu'_F(U(x))$ is called membership degree of $x \in \mathbf{R}^3$ in F'.

As a result, we can get the definitions of flow feature region and core further:

Definition 2: Feature Region (FR): Assume F^{i} is the i th

feature region, D_{F^i} and $D_{F^i} = \left\{ x \middle| \mu_F' \left(U(x) \right) > \alpha \right\}$, where α is the limit reference defined by the user.

Flow feature region i is different in $\mu'_F(U(x))$ with other region. For calculating membership degree in any point x in the data, it is necessary to define related feature mapping rule:

Definition 3: Extract Rule (ER): Assume any point $x \in \mathbb{R}^3$ in the flow, the mapping function $F(\Phi(x), \Upsilon(x), \Pi(x)) \mapsto [0,1]$ is named as the i th feature region extract rule.

Moreover, we further take into account of the relationship between different features in practice for users may be interested in more than one feature. So it is needed to introduce the logic operations between deferent features.

Definition 4: Logic Operation (LO): Assume R_{F^i} and R_{F^j} is the different 3D flow feature region i and j, the logic operations \neg , \land , \lor are defined in section 2.2.2.

Based on the above definitions, we get the fuzzy-based flow feature description model as showing in Fig. 1.

Basic Property: attributes which describe the basic space and orientation information, include space variable (3D coordinate system) and velocity vector.

Derived Property: attributes calculated from existing attributes, such as vortex magnitude, velocity gradient tensor, and so on.

Associated property: attributes other than basic attributes and derived attributes in the datasets, such as temperature, pressure and density.

The properties above compose Flow Property.

Fuzzy Theory: In FFDL, we mainly use c-mean fuzzy cluster [7].

Extract Rule: include Flow Property and Fuzzy Theory.

Proportion Ration: the importance degree of the extract rules.

Flow Feature: What we get after using one or more Extract Rules.

Logic Operations: in fuzzy theory,

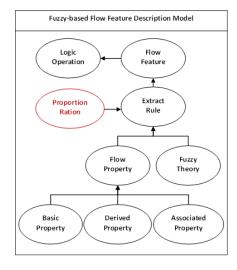


Fig. 1. Fuzzy-based Flow Feature Description Model

$$\neg a = 1.0 - a$$

$$\land (a,b) = \min(a,b)$$

$$\lor (a,b) = \max(a,b)$$
(2)

where a and b are variables.

After the fuzzy-based flow feature description model, we introduce the FFDL description criterion and semantic framework.

1) Description Criterion

The basic symbols used in FFDL are:

Constant symbols: $a,b,c,...,a_1,b_1,c_1,...$

Variable symbols: $x, y, z, ..., x_1, y_1, z_1, ...,$

Function symbols: $f, g, h, ..., f_1, g_1, h_1, ...,$

Predicate symbols: $F, G, H, \dots, F_1, G_1, H_1, \dots$

Conjunction symbols: \neg , \wedge , \vee , and

Atom feature symbols: $FF_1, FF_2, FF_3,...$

Constant and variable in FFDL denote flow attribute; function includes membership degree mapping functions and fuzzy operators; Predicate contains flow feature attributes estimation (such as whether the point x is belong to feature region i and the membership degree) and comparisons between different features; Conjunction is the logic operations. Based on the above, we introduce the item and formula in FFDL.

Definition 5: Constant and variable are items, which are flow attributes in practice.

Definition 6 Formulas in FFDL:

- (1) If FF_i is the n D atom feature name and $x_1, x_2, ..., x_n$ is items, $FF_i(x_1, x_2, ..., x_n)$ is formula;
- (2) If α is formula, $\neg \alpha$ is formula;
- (3) If α and β is formula, $\alpha \wedge \beta$ and $\alpha \vee \beta$ are formulas;
- (4) The result of finite iteration of (1-3) is formula.

Formulas in FFDL indicate the description of the flow feature, so they are called Feature Formula too.

2) Semantic framework

We can get any feature from Definition 6, whose semantic explanation as follows:

Definition 7: One explanation of FFDL is $I = \{D, I_0\}$, in which

- i) Non-empty set D is individual domain of I;
- ii) F_0 is a mapping defined as:
 - a) If c is individual constant, $I_0(c) \in D$,
 - b) If f is individual function constant, $I_0(f): D^n \to D$,
 - c) If p is proposition constant, $I_0(p) \in [0,1]$, and
 - d) If P is Predicate constant, $I_0(P): D^n \rightarrow [0,1]$.

Moreover, we need to explain variables in FFDL:

Definition 8: One explanation of FFDL is $I = \{D, I_0\}$. If mapping σ is defined as follows:

- i) If x is individual variable, $\sigma(x) \in D$,
- ii) If f is individual function variable, $\sigma(f): D^n \to D$,
- iii) If p is proposition variable, $\sigma(p) \in [0,1]$, and
- iv) If *P* is Predicate variable, $\sigma(P): D^n \to [0,1]$.

 σ is called an assignment under I .

Definition 9: The explanation of Formulas:

$$\neg \left(\mu'_{F_{i}}(U(x)) \right) = 1.0 - \mu'_{F_{i}}(U(x))$$

$$\land \left(\mu'_{F_{i}}(U(x)), \mu'_{F_{j}}(U(x)) \right) = \min \left(\mu'_{F_{i}}(U(x)), \mu'_{F_{j}}(U(x)) \right) (3)$$

$$\lor \left(\mu'_{F_{i}}(U(x)), \mu'_{F_{j}}(U(x)) \right) = \max \left(\mu'_{F_{i}}(U(x)), \mu'_{F_{j}}(U(x)) \right)$$

And the corresponding framework of FFDL is shown in Fig. 2. where

- DataSource: The source of the data.
- FeatureSets: Sets of multi-features,
- Features: The interested attributes or structure of the data.
- · ExtractRule: Rules for extracting features, and
- FuzzyOperator: ContainsDiffuseOperator and ConcentrateOperator.
- ProportionRation: The importance degree of the extract rules.

More details about framework of FFDL see [5].

2.2 Extract Rules

We give several extract rules for specific feature. In order to get a better hierarchy structure of logic, each extract rule will be composition of the three types of attributes. And each extract rule can choose any attribute(s) in the data.

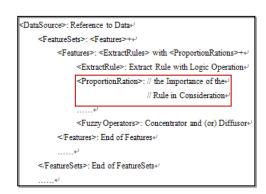


Fig. 2. Framework of Optimized FFDL

For explain the extract rule clearly, we introduce Membership Operator first.

Membership Operator: a variable derived from some extract rule to measure the size of the membership degree.

Some of the extract rules of vortex are as follows.

Helicity Rule: Levy et al. [17] used normalized helicity, H_n , to extract vortex core lines.

$$H_n = \frac{v \cdot \omega}{|v| |\omega|} \tag{4}$$

 H_n is the cosine of the angle between velocity, v, and vorticity, ω . There is a underlying assumption that the angle between v and ω is small near vortex core regions. If $v \square \omega$, $H_n = \pm 1$. And the streamline which passes through that point has zero curvature.

Because H_n is always smaller than 1, it is no need to be normalized. So the Membership Operator is

$$H_{nSMD} = H_n = \frac{v \cdot \omega}{|v||\omega|} \tag{5}$$

Streamline Distance Rule: Four order (two order in real-time interaction) Runge-Kutta method is used to calculate streamline distance Membership Operator as follows:

$$d_{sISMD} \begin{cases} 1 - \int_{x_1}^{x_2} df & \text{if streamline } f \text{ comes} \\ & \text{through } x_1 \text{ and } x_2 \\ \infty & \text{else} \end{cases}$$
 (6)

 λ^2 **Rule**: Jeong and Hussain [18] introduced a definition of

```
DataSource>D:\\Project\\data\\spacecraft1\\14000 flow-UVW.raw
    <FeatureSets>Vortex+
         <Feature>VortexRegion↔
               <LogicOperation>AND↔
                    <ExtractRule>VelocityER+
                    < ProportionRation>VelocityPR↔
                    <ExtractRule>StreamlineDistanceER↔
                    < ProportionRation>StreamlineDistancePR
                    <ExtractRule>Lambda2ER↔
                    < ProportionRation> Lambda2PR+
                    <ExtractRule>PressureER↔
                    ProportionRation>PressurePR+
                    <ExtractRule>TemperatureER↔
                    < ProportionRation>TemperaturePR+
               </LogicOperation>+
               <FuzzyOperators>↔
                    <DiffuseOperator>VR DiffuseOperator√
                    <ConcentrateOperator>VR ConcentrateOperator
              </FuzzyOperators>↔
         </Feature>+
    </FeatureSets>+
```

Fig. 3. Application of FFDL

a vortex which is always called λ^2 definition. The authors

think that a pressure minimum is not sufficient as a detection criterion. Because unsteady irrotational straining can create a pressureminimum without a vortex, and viscous effects can eliminate the pressure minimum in a vortex. In order to remove their effects, they decompose the velocity gradient tensor ${\bf J}$ into its symmetric part ${\bf S}$ and antisymmetricpart ${\bf \Omega}$. They define a vortex as a connected region where ${\bf S}^2 + {\bf \Omega}^2$ has two negative eigenvalues. Let λ_1 , λ_2 , λ_3 be the eigenvalues such that $\lambda_1 \geq \lambda_2 \geq \lambda_3$, [2] introduced that the region where $\lambda_1 \leq 0$ is vortex region too. So the Membership Operator is [2]

$$\lambda_{2SMD} = \begin{cases} 0 & , \lambda_2 \ge 0 \\ 1 & , \lambda_1 \ge 0 \\ scale(-\lambda_2), \text{else} \end{cases}$$
 (7)

where scale(*) is normalization operation.

2.3 FFDL Application

Based on Section A, we got a more practical FFDL application by using it in vortex extraction and visualization. Fig. 3 is the FFDL demo for vortex region extraction. The extract rules are utilized to calculate the membership degree of data points, and every extract rule has a ProportionRation.

Then, we use this to optimize the interactive fuzzy-based feature extraction and visualization algorithm IFRFE [5]. The algorithm flow is shown in Fig. 4.

STEP 1: Preprocessing

- Data readin: get the raw data; extract the needed data attributes according to the feature extraction, includes position, velocity, pressure etc.
- Feature attributes calculation: calculate basic flow attributes to be used by the extraction rules. For example, we can get feature value after calculating velocity gradient tensor.

STEP 2: Feature calculation

- Feature definition: User defines the interested features, such as vortex, shock surface, and so on.
- Membership degree calculation: According to the selected feature(s), users can easily modify the extract rules, proportion rations and fuzzy operators by UI until the satisfied results are generated.

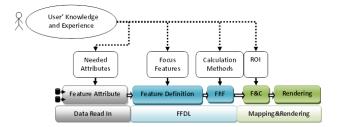


Fig. 4. Flow of IFRFE [5]

STEP 3: Feature rendering

Mapping and rendering: calculate color and transparency of particles according to the membership degree.
 Users can not only define the needed attributes and features, but also easily choose the region of interested (ROI).

III. EXPERIMENTAL RESULTS AND ANALYSIS

We use desktop with Intel Pentium Core 1.86GHz CPU and NVIDIA GeForce 9800 GTX GPU (512MB memory). Our development environment is Visual Studio 2005 and Qt 4.7.2 to implement UI and part of interaction (see Fig. 9).

In order to verify the optimized FFDL and IFRFE [5], we process datasets from different subjects and applications.

3.1 Capsule Dataset

Capsule dataset contains complex vortex structure. Fig. 5shows the results of IFRFE. It is necessary to reemphasize that users can easily modify operators to get satisfied outcome. In Fig. 5(a), the ProportionRation of streamline distance rule and λ_2 rule are 0.1 and 0.9 individually. We can see the vortex core in red and context in green. In Fig. 5(b), the ProportionRation of streamline distance rule and λ_2 rule are 0.9 and 0.1 individually. We can see paths where particles leave vortex. In Fig. 5(c), the ProportionRation of velocity, streamline distance, λ_2 , pressure and temperature rules are 0.1, 0.1, 0.1, 0.1 and 0.6 individually. At this time, we can not only see the vortex region, but also see the high pressure region. (See red region) In Fig. 5(d), the Proportion Ration of velocity, streamline distance, λ_2 , pressure and temperature rules are 0.1, 0.1, 0.1, 0.6 and 0.1 individually. Now it is easy to notice the relation between low pressure and vortex region. (See red region.)

This shows that IFRFE can not only automatic calculate

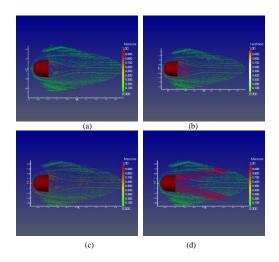


Fig. 5. Extract Rule in IFRFE

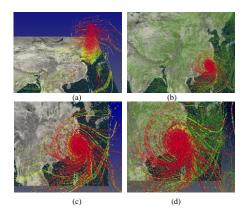


Fig. 6. Typhoon Datasets (Color Plate 9)

several extract rules, but also allow users to interactive modify the extracted features. What is more, users will visually find important relationships between different physic phenomenon. While traditional single extract rule cannot reach this.

3.2 Typhoon Dataset

Fig. 6 shows the results of typhoon dataset by IFRFE. In Fig. 6(a), red region is the core of the typhoon, and particle trajectories show that high-altitude air spirals down into the eye and then spreads outward as shown in yellow particles. In Fig. 6(b), it is clear to watch the movement of the core of typhoon. Fig. 6(c-d) gives particular local views of the key feature without and with context particles respectively. By the interactive way, users can easily get the Ben Shneiderman's visual-information-seeking mantra:" Overview first, zoom and filter, then details-on-demand." [8].

3.3 Lorenz Dataset

We do not only apply our algorithm in practical datasets, but also test it with physics models, such as Lorenz model as shown in Fig. 7. Lorenz model has important implications for climate and weather prediction. The model is an explicit statement that planetary and stellar atmospheres may exhibit a variety of

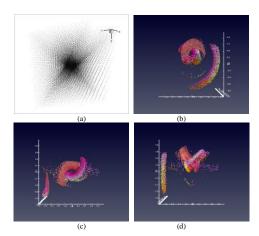


Fig. 7. Lorenz Dataset

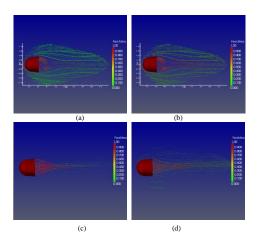


Fig. 8. Interactive Visualization

quasi-periodic regimes that are, although fully deterministic, subject to abrupt and seemingly random change. In Fig. 7, (b-d)are different views of the feature extraction results of Lorenz dataset. In practice, we make use of animation of particles to visualize this data. And it is very helpful for users to understand the dataset. Fig. 7(a) is the same data plotted by Tecplot 2010, where it is hard to see features in the datasets.

3.4 Interaction in Real-time

As an interactive visualization algorithm, IFRFE commonly interactive means such as linked views, F&C and multiple views to inspires users to get into their datasets. Moreover, users can use 2D slice (Fig. 8(a-b)) to see part of the features and avoid occlusion in 3D (Fig.8(c-d)).

IV. CONCLUSION

An optimized fuzzy-based algorithm is introduced to interactively extract features from 3D flows in practice. Compared-with the traditional methods, our algorithm could extract features more precisely. Experimental results of datasets from different applications and models demonstrate the correctness, effectiveness and interaction of the algorithm.

In the future, we will extend IFRFE to other CFD features, such as shock surface, separation and attachment lines. On the other hand, 3D interaction mode which takes use of 3D interaction and display devices and force feedback theories will be adopted further.

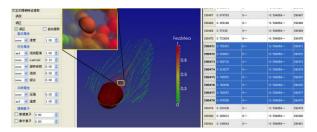


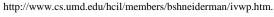
Fig. 9. Fuzzy-based Interactive Feature Extraction

ACKNOWLEDGEMENT

The authors would like to thank the anonymous reviewers for their helpful remarks. This work was supported in part by the National Natural Science Foundation of China under Grant No. 60873120, 61170157, and the National Grand Fundamental Research 973 Program of China under Grant No. G2009CB72380.

REFERENCES

- R.Burger, P.Muigg. (2007). M.Ilcik, H.Doleisch and H.Hauser, "Integrating Local Feature Detectors in the Interactive Visual Analysis of Flow Simulation Data", In Proc. EuroVis 2007, pp. 171-178.
- [2] H.Doleisch, M.Gasser and H.Hauser. (2003). "Interactive feature specification for focus+context visualization of Complex Simulation Data", In Proc. VisSym 2003, pp. 239-248.
- [3] C. Johnson. (2004). "Top Scientific Visualization Research Problems", IEEE Computer Graphics and Applications, 24(4) pp. 13–17.
- [4] B.H. McCormick, T.A. DeFanti and M.D. Brown. (1987). Visualization in Scientific Computing, eds., ACM Press.
- [5] Enya Shen, Huaxun Xu and Sikun Li, "Fuzzy-based Feature Description Language and Interactive Extraction of Features in 3D Flows", *Journal of Simulation System*, in press.
- [6] Zesheng Tang, Li Chen and Junhui Deng. (1999). Visualization of 3D data sets, Tsinghua University Press, Beijing.
- [7] Xinbo Gao. (2004). Fuzzy clustering analysis and application. Xi'an University of Electronic Science and Technology Press, Xi'an: 49-54.
- [8] B. Shneiderman, "Information Visualization: Dynamic Queries, Starfield Displays, and LifeLines", white paper,





Enya Shen received hisM.Sc. degree in Computer Science from the National University of Defense Technology in 2010. Currently he is a doctoral student at the College of Computer Science and Technology of the National University of Defense Technology. His research interests include flow visualization, interactive visualization and human-computer interaction.

Huaxun Xu is a researcher in ArmyAviation Institute of PLA, China,and a Ph.D. candidate in nationaluniversity of defense tech-

Ph.D. candidate in nationaluniversity of defense technology. His current research interests includes scientific visualization and virtual reality technologies.

Wenke Wangis an associate professor in School of Computer at National University of Defense Technology. He received a BS and a PhD in computer

science and technology from Tsinghua University, China, in 2003 and 2009, respectively. His research interests include curves and surfaces, geometric modeling, and scientific visualization.





Xun Cai, born in 1971, is an associateprofessor and senior member of ChinaComputer Federation. His main researchinterests include scientific visualization.



Zeng Liang, born in 1970, is an associateprofessor and senior member of ChinaComputer Federation. His main researchinterests include parallel simulation, virtual reality and visualization.



Sikun Liis a professor at the College of Computer Science and Technology of the National University of Defense Technology. He is the principal of many national research projects of China such as the National Science Foundation program, the National High Technology Research and Development program and the National Basic Research program. His research interests include scientific visualization, virtual reality, very large scale integration, and the design of SoC.