NONLINEAR DYNAMICS FOR CLASSIFICATION OF MULTIPHASE FLOW REGIMES

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Abstract

The problem of identification of flow regimes in processes involving multiphase mixtures (nuclear plant, fluidization, hydrocarbons, chemical reactors) is an open problem for many industrial applications. Generally, different flow regimes induce different performances of the system. Due to the highly non-linear nature of the forces which rule the flow regime transitions, the prediction is really difficult. The most utilized approach, is to identify the actual flow pattern from signal analysis of sensors which fluctuation is related to the flow regime structure. Many studies have been carried out in this direction using different sensors and different analysis techniques.
This study can be considered in this frame of research. Our goal is to show the potential of a new analysis technique based on non-linear dynamics trough the morphological desciption of the reconstructed attractor.
We explain the main approaches to this problem in the Literature, the derivation of the proposed technique and compare this technique with the other classical and non-linear approaches.

1. State of the art of multiphase flow pattern recognition

In this paper, we will limite this analysis to the studies regarding two/three phase flows, gas-liquid, in straight tubes and we will give a specific attention to the non-linear approaches.
In the years ‘66-‘90, the problem of gas-liquid flow regime recognition was carried by several researchers following two main directions: the Probability Density Function (PDF) and the Spectral Analysis of the signals of local sensors [Hubbard & Dukler 1966; Jones & Zuber 1975; Vince & Lahey 1982; Tutu 1982 1984; Matsui 1984, 1986; Lin & Hanratty 1987, Annunziato 1988]. From PDF, they derived a series of parameters related to the shape of this function like statistical moments. From Spectral Analysis the discriminants are derived from the Auto Power Spectral Density or other functions related to the Fourier analysis (CPSD, Phase, Coherence, Cepstrum, Cross-Correlation). Generally, these studies conclude the analysis with a specific set of thresholds on the proposed discriminants, in order to distinguish the flow regimes. In most of the cases these thresholds satisfy very well the experimental data they tested. The main limit consists in the impossibility of extend the same thresholds for different fluids, sensors or plants. The reason is that the linear approach takes into consideration the average statistical of the signal which are not invariant in respect to some process parameters (sensor response, fluid density, fluid viscosity, wall roughness) which are very important in the flow dynamics.
In order to bypass these limits some researchers have try to use non-linear approaches.
Both the studies of Franca et al. [1991] and Djainal et al. [1995] utilized the fractal dimension as an invariant which could be independent from fluids. They utilized several definitions of this invariant: the correlation dimension introduced by Grassberger and Procaccia [1983], the Hurst dimension [Mandelbrot 1982, Franca et al. 1991] and the definition of Higuchi [1988] . Both these studies were able to the demonstrate the better

performances of fractal dimension in respect to the PDF and APSD parameters. They indicate some ranges of values for the fractal dimension in various flow regimes. Because of the flow regime classes are not separated, the ranges are very similar and the measurements is very connected to the method utilized for the computation of the fractal dimension. In conclusion, the main limit of these studies is that they were not able to avoid thresholds which could be still connected with sensors, fluids and computation method.

2. Setting of the problem

This study is in the framework of a project financed by EU (Thermie Project) for monitoring and diagnostics of oil plants. The data presented in this paper come from an experimental loop located at ENEA (OIL facility) working at low pressure (10 bar) with three phases: air, water and a synthetic oil (density and viscosity similar to the real oil). The test section is composed by a complex system for measurement of the multiphase flow rates which use the flow regime information in order to drive the analysis modeling. This system (Multiphase Expert Flowmeter) use a dual energy gammadensitometer and a venturimeter with two differential pressure transducers: one on the convergent nozzle and the other on the divergent one. The MEF system is installed on a vertical channel with upward flow of 77 mm diameter. We have used the signal of the differential pressure transducer installed in the divergent part of the venturimeter in order to identify the flow regime. The sampling frequency is 200 Hz (200 seconds of acquisition) and we have filtered the signal with a moving average filter (recommended for nonlinear analysis, Abarbanel 1996) in order to reduce the external noise. Finally we have normalized the signal with zero mean and standard deviation equal to one.
The test matrix is composed by a series of about 70 tests with a wide range of oil, water and gas flow rates including three different flow regimes (bubble, slug, churn). In the following, we give a synthetic description of the flow regimes for the vertical upward flow.

Bubble flow: little gas bubble flow in a continuum of liquid.
Slug flow: the flow is composed alternately by liquid slugs (with little gas bubbles) and large gas bubbles (*Taylor Bubble*) which occupy most of the section of the channel; a liquid film is present on the wall of the Taylor Bubbles.
Churn flow: the flow is intermittent. Liquid and gas are mixed and jump up and down in the channel producing density waves.
Annular flow: the gas flows mainly in core of channel and the liquid form a annular film on the wall characterized by waves on the separation interface.
In order to verify the accuracy of the classification we have compared the response of the method we propose with the experimental flow regime. The experimental flow regime is derived from the analysis of a multiple optical fibre sensors with 8 probes along the diameter of the channel. These probes give the istantaneous phase (gas or liquid) which is present on a very little sensible tip (0.5 mm). From these measurements it is quite easy understand the internal structure of the flow regime. Obviously this sensor is intrusive and fragile and it cannot be utilized for industrial applications. In that case we use the venturimeter or a simple differential pressure transducer like that one included in the MEF system which is, at the moment, installed and operating at the Trecate oil field of AGIP.

3. Basic non linear analysis

The starting point of our analysis is the attractor reconstruction in the embedded pseudo-phase space. The reconstruction procedure is based on Takens embedding theorem [1981]. The attractor is obtained using the signal values delayed of a time lag which is characteristic of the system. The reconstruction procedure consists in the determination of the optimal time lag and the identification of the dimensionality of the system.

In the nonlinear dynamics Literature, several methods have been developed in order to determine these parameters. The time lag is derived by the Average Mutual Information (AMI) and dimension is derived by the Global (/Local) False Nearest Neighbors (GFNN/LFNN). In Abarbanel 1996, the main techniques for these computations are reported.

We used a tool (CSP) developed by the Institute of Nonlinear Science (UCSD, Ca) in order to compute these parameters.

The results indicate an optimal time lag of about 50-200 msec, global dimension of 5-6 and local dimension of 4-5. The results depend by flow regimes and flow rates.

4. The description of the attractor shape

In order to classify the dynamic differences between different flow regimes we developed a new method which is described in the following. This method is based on the observation of morphological differences on the shape of the attractor. Although the system has a dimension of 4-5, the morphological differences are evident also projecting the attractor in two dimensions. In fig. 1 some attractors in three different flow regimes are reported.

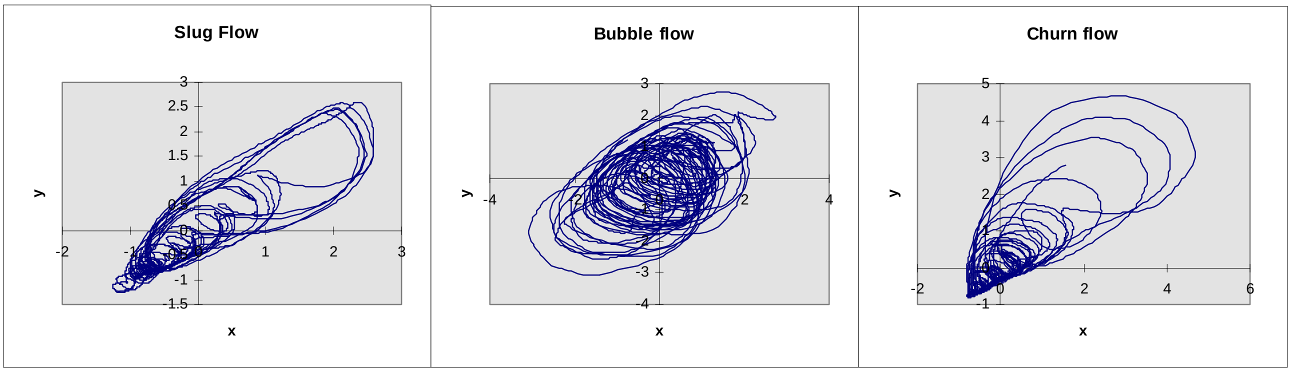


Fig. 1 : Attractor typical shape for different flow regimes.

The description of the attractor shape is quite difficult because it depend strongly by the time lag utilized in the reconstruction of the embedded space. In fig. 2, an example of this effect is reported. The determination of time lag from the first minimum of the AMI, as suggested by several authors [Fraser, Swinney, 1986] is very uncertain in our case where a clear minimum is never present.
The use of different time lags for each test can induce large errors connected to an not exact choice of the time lag. The use of a constant time lag is not correct because each test has its specific lag.
This lag is connected not only to the flow regime but it depends also on the mixture velocity which can induce a time contraction or expansion of the dynamics. It is possible to have two tests related to different flow regimes with similar time lag and two test related to the same flow regime with very different time lags. The problem is: it is possible to have a morphological descriptor of the attractor which is invariant in respect to the time lag ?

To give an answer to this question we have built a series of shape descriptors and analyzed their evolution varying the time lag. In this study we report an analysis based on two-dimensional descriptors, but the analysis is easily extensible to higher dimensions.
As shape descriptors we have choice the geometrical moments of the attractor in respect to two main axes: the bisector of the first-third quadrant (see fig. 1) named *principal axis*, and the bisector of the other quadrants named *secondary axis.* The moments are defined as following.

Moment of order i in respect to the principal axis:

$$M_i^+ = \frac{\sum_{j=1,N} (d_j^+)^i}{N}$$

Moment of order i in respect to the secondary axis:

$$M_i^- = \frac{\sum_{j=1,N} (d_j^-)^i}{N}$$

where d^+ is the distance from the principal axis and d^- the distance from the secondary axis, N the number of points in the signal:

$$d^+ = \frac{(y-x)}{\sqrt{2}} \qquad\qquad d^- = \frac{(y+x)}{\sqrt{2}}$$

where x, y are the coordinates of the embedded.
Starting from time lag equal to zero, the attractor is compressed on the principal axis (fig 2). The M_i^+ are equal to zero and the M_i^- are equal to the linear statistical moments multiplied for $\sqrt{2}$. Increasing the time lag, these moments describe the morphological evolution during the unfolding process of the attractor.

The moments evolve from the linear value to nonlinear one. Finally we can outline that the even moments are ever positive and describe the scatter of the attractor; the odd moments are symmetry descriptors. It is possible also compute mixed moments like the following:

$$M_{4R} = \frac{\sum_{j=1,N} (d_j^{\,+})^3 \cdot (d_j^{\,-})}{N}$$

This is a descriptor of the symmetry in respect to the principal axis, but the zones of the attractor which more distant from the secondary axis are more weighted.

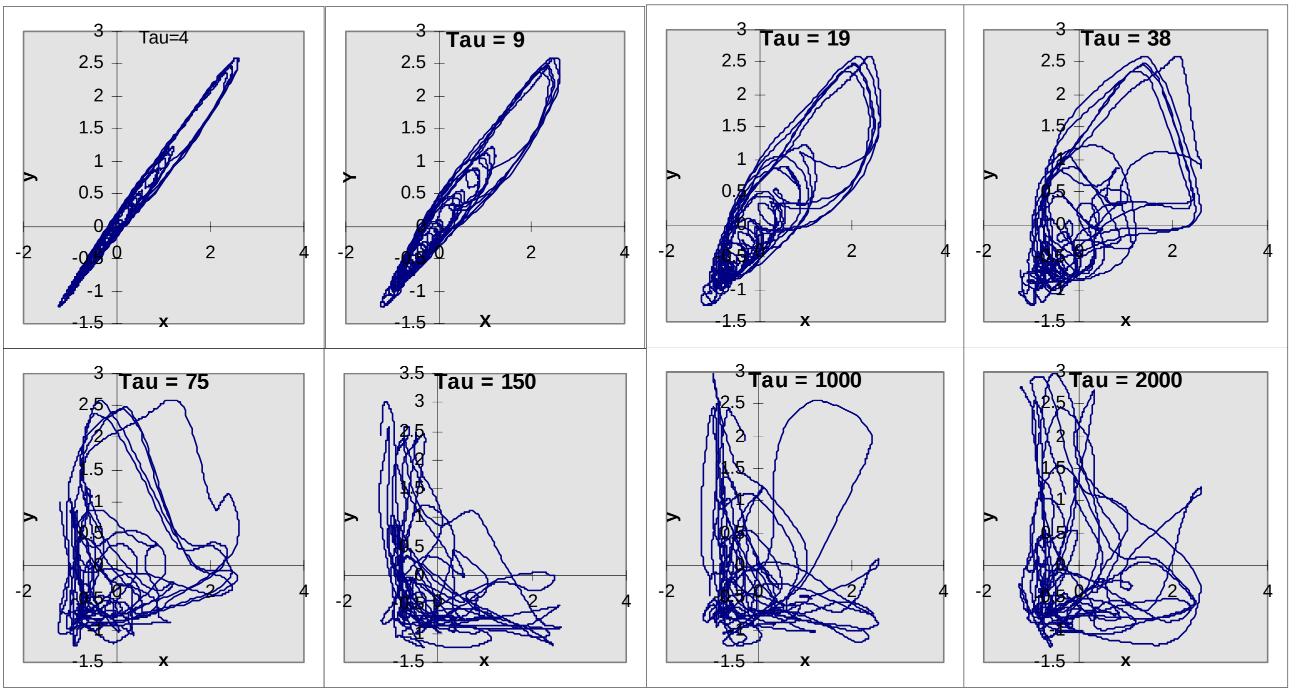
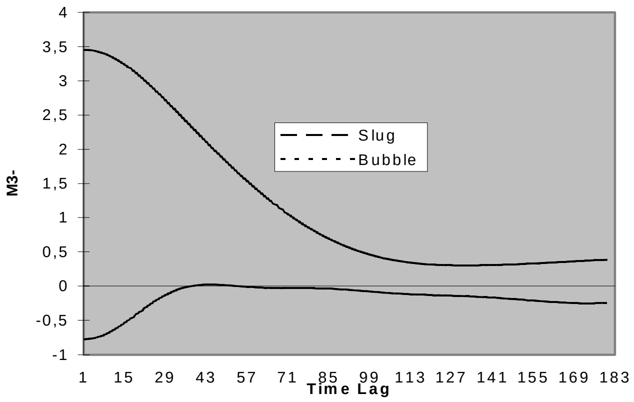


Fig. 2 : Attractor shapes during the unfolding process (increasing the time lag) in a condition of slug flow

5. The Unfolding Descriptors

Computing the moments for different time lag we obtain a curve like that ones reported in fig. 3.
For the most significative moments (we have computed (i=2,3,4, +/- and several mixed moments) we have obtained a similar shape of the curve reported in fig. 3. The curve is composed by a first zone approximately linear; it reaches a first maximum or a minimum at a time lag of about 20-50 and then, in the second zone, it fluctuates in an pattern not correlated.
If we analyze the attractor shape during this evolution, the first zone corresponds to the emergence of the attractor structure and the second zone corresponds to a

degenerative process in which the attractor loss the coherence in the trajectories and it assume a typical shape which is shown for very high (not correlate) time lags.
From this analysis we conclude that a) the first zone is very stable and it represents the unfolding process from the linear contraction to the nonlinear structure, b) the first maximum (or minimum) represents a *transition lag* in which the process of genesis of the structure of the attractor is inverted.
At the moment, the relation between the *transition lag* and the optimal time lag it is not much clear tough a strong relation is expected.
As an clear example of the potential of information included in the first zone of the nonlinear moments versus the time lag, we compare the curve of the M_3^- of bubble flow and the curve of the slug flow (fig. 3). It is impressive that almost all the tests in bubble flow show a curve ascending in the first zone while the tests in slug flow show a curve descending in the first zone. In a similar way the M_{4R} moment is ascending for almost the tests in slug flow and descending in the tests of churn flow (fig. 4).
Finally we can introduce the definition of the *unfolding descriptors* as the slope of the first linear zone of the curves of the nonlinear moments. In our case, all the tests show a very clear first maximum or minimum and we compute the slope as the linear regression from 0 up to the transition lag. In the cases where the first maximum or minimum is not so evident a more accurate algorithm has to be used.



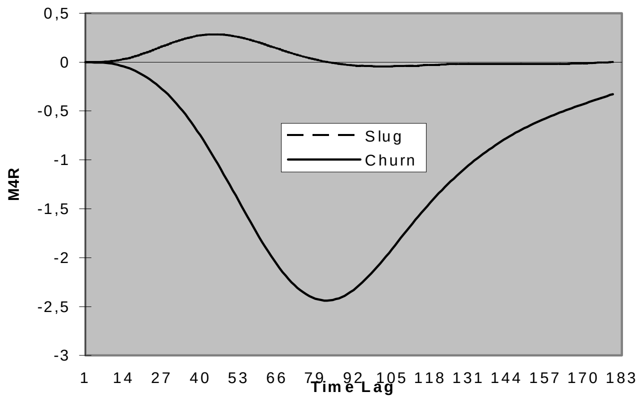


Fig. 3, 4 : Typical trends of the two nonlinear moments utilized for the flow regime classification.

6. Results

Only two descriptors have been sufficient in order to reach a very good results in terms of flow regime classification. In fig. 5 are reported the results of the two descriptors utilized (M_3^- and M_{4R}) ; the experimental flow regime are represented with different test symbols. It is evident that the three classes result very distant and separated in this classification space. This is remarkable, considering that the classes are adjacent in terms of flow rates. This means that these parameters strongly amplify the differences in the dynamics.
The second evidence is that it is not necessary fix thresholds because the natural thresholds are located at zero: the unfolding of the attractor for different flow regimes goes in different directions in terms of shape descriptors.
Assuming a very simple classifier with the zero lines as the classes separation, we obtain an efficiency of about 93 %. Going a bit more deeply, we have detected five errors and we have realized that four of these errors are located exactly in the transition zones (three for slug-churn and one for slug-bubble). To analyze better the transition conditions we have computed the unfolding descriptors for a reduced time (8000 samples instead 40000 available) and moved this time window in the signal, shifting 2000 samples at the time. In fig. 6 are reported the results of this analysis for the M_3^- parameter. The plot shows a typical condition of slug flow, a typical condition of bubble flow and a test in the bubble-slug transition zone. The zero line represents the classes separation. It is interesting to observe that the transition condition is recognized as an alternately

presence of bubble flow and slug flow. This is really what it happens in the transition zone when some sporadic slugs are generated in a continuum of bubble flow.

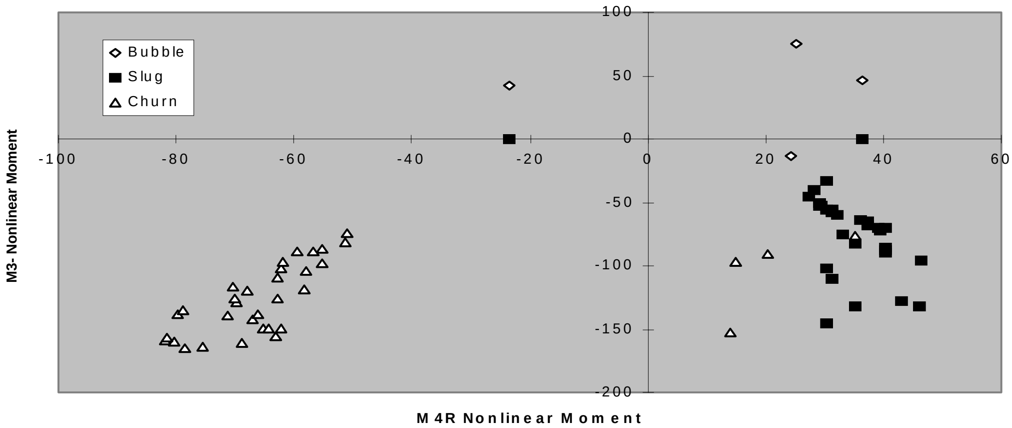


Fig. 5 : Classification Map with Unfolding Descriptors

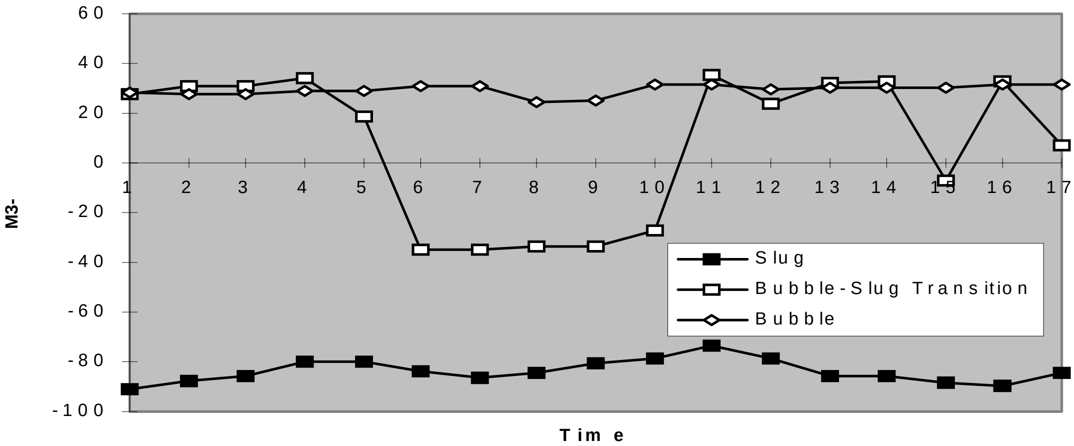


Fig. 6 : Transient Computation of the M3- Nonlinear Moment for slug flow, bubble flow and for a transition condition.

Using the transient analysis we have explained (the transition is identified when a second regime is detected for more than 20 % of the measurement) we were able to increase the accuracy of the flow regime identification at 98 % (only 1 error).
We have compared this technique with the classical Fourier analysis and the fractal dimension.
In a previous study [Annunziato 1988] we have developed a tool for flow pattern recognition which use 5 discriminants, -derived from PDF, APSD, Cross-Correlation- in order to identify vertical upward gas-liquid mixtures from differential pressure signals. Although the abundance of discriminants, the recognition efficiency has resulted of 93 %. Furthermore, all these discriminants are characterized by ranges which have a partial interference between several flow regimes and are probably related to the fluids characteristics.
In order to check the methods utilized in the previous nonlinear approaches we have computed the fractal dimension following the definition of Grassberg and Procaccia [1983] and using the CSP tool [Abarbanel 1996].
The results of these computations are very uncertain because of strong changes in the fractal dimension

depending the mean radius (fraction of the attractor size). These effect is probably due to a little percentage of noise present in the signal. This effect is often revealed in studies on real data and this invariant is not recommend in presence of a lit amount of noise [Abarbanel, 1996].

7. Conclusions

The main conclusion is that the proposed approach, based on the description of the morphology evolution of the attractor in its unfolding process, has a very interesting potential for identify the classes of behavior of a system.
In the specific case of gas-liquid upward flow we are able to demonstrate the superiority in the flow regime identification in respect to the classical Fourier or PDF analyses and in respect to the Fractal approach. More investigations are necessary to verify the possibility to extend these conclusion to other conditions. More investigation are also necessary in order to understand the physical meaning of the transition lag and the possibility to extend to higher dimensions.

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