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# Signals Features Extraction in Radioisotope Liquid-Gas Flow Measurements using Autocorrelation Function

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***Abstract* - Knowledge of the two-phase flow structure is essential for the proper conduct of industrial processes. Description of liquid-gas flow regimes is possible by using of data analysis in time, frequency, or state-space domain. In this research studies, the autocorrelation function is applied for analysis of signals obtained for liquid-gas flow by use gamma-ray absorption. The experiments were carried out on the laboratory hydraulic installation fitted with Am-241 radioactive source and scintillation probe with NaI(Tl) crystal. Four types of flow regimes as plug, slug, bubble, and transitional plug – bubble were studied in this work. It was found that the selected amplitudes of the normalized autocorrelation function are helpful to recognize the flow regime.**

***Keywords – two-phase flow, gamma-ray absorption, autocorrelation function, features selection***

## I. Introduction

Knowledge of a liquid-gas flow structure is important for the appropriate conduct of many processes in the industry (e.g., in the mining, nuclear, petrochemical, energy, and environmental industries). Much work has been done to identify the flow regime, e.g. [1-6]. Recent publications describe application for this purpose computational intelligence methods as, e.g., expert systems and artificial neural networks [7-12]. Generally, machine learning methods exploit various features of signals in the state-space, time, and frequency domains. In the time domain, statistical parameters of signals are used, such as mean value, RMS, skewness, kurtosis, variance, and higher-order moments [7]. Important signals features in the frequency domain can be appointed by use the wavelet transform, Fourier Transform, STFT or other methods [10, 13].

In this paper, the autocorrelation function (ACF) is applied to the analysis of signals obtained in water-air flow measurements by use gamma-ray absorption. The data were registered in experiments made using the laboratory set-up with a horizontal pipeline. Signals collected for four regimes of liquid-air flow as a plug, slug, bubble, and transitional plug – bubble one are recorded. The obtained signals were analyzed and the selected parameters of normalized ACF were extracted.

## II. Idea of Gamma-absorption Method and Laboratory Stand

The gamma-ray absorption technique is based on the exponential decay of a γ radiation beam in function of the geometry and composition of the absorbent [1]. The changes in the intensity of radiation are detected by the scintillation detectors and converted into electrical pulses.

The typical γ-ray set for two-phase flow measurement is shown in Fig. 1.

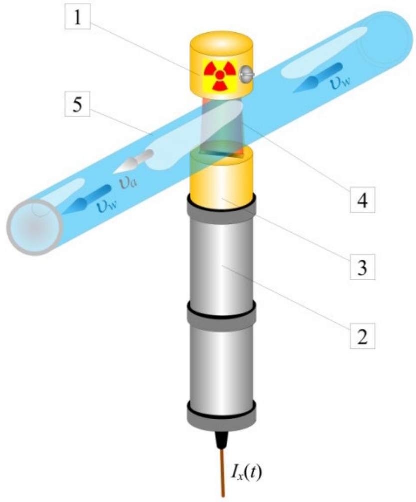


Figure 1. The principle of γ absorption method: 1 – gamma ray source in the collimator, 2 - scintillation detector, 3 – collimator of the detector, 4 – γ-ray, 5 - pipe, $\upsilon_a$ – gas velocity $\upsilon_w$ – liquid velocity

The radioactive source (1) emits the γ radiation beam (4) shaped by a collimator. Gamma photons pass through the pipeline (5) and liquid-gas flow. The scintillation probe (2) with a collimator (3) is placed on the other side of the pipe.

In the presented experiment, the following measurement system configuration was used: a linear Am-241 source emitting photons with an energy of 59.5 keV and a detector with NaI(Tl) crystal. At the output of the detector, the count signal $I_x(t)$ was registered using a dedicated counter card.

The gamma absorption set described above was used in the experimental stand, constructed in AGH University of Science and Technology in Krakow. A detailed description of the hydraulic set-up can be found in [7,13]. The main element of the installation is a horizontal plexiglass pipe with an internal diameter of 30 mm and a length of 4.5 m. General view of the measurement section of the installation is shown in Fig. 2.

Figure 2. Measurement section of the installation

Figure 3 shows examples of the analyzed flow regimes: slug (experiment LIQ1), plug (LIQ4), transitional plug – bubble (LIQ7) and bubble (LIQ10).

(a)

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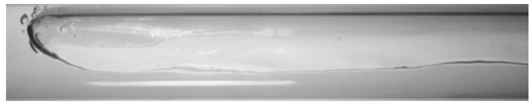

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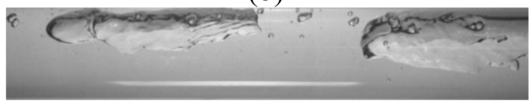

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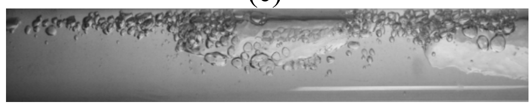

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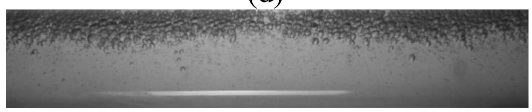
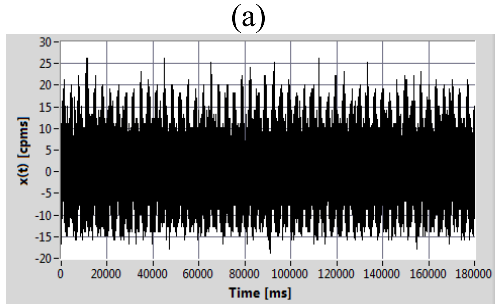


Figure 3. An examples of the analyzed flow regimes: (a) slug, (b) plug,
(c) transitional plug – bubble, (d) bubble

The DAQ system contains a counter card connected to the PC using a USB port. Voltage impulses $I_x(t)$ are registered within the sampling interval $\Delta t$ =1 ms and create signals $x$(t). Figure 4 shown time records of the signals obtained in the mentioned above experiments (after centering operation).

(a)

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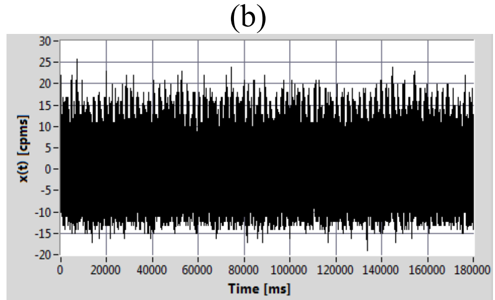


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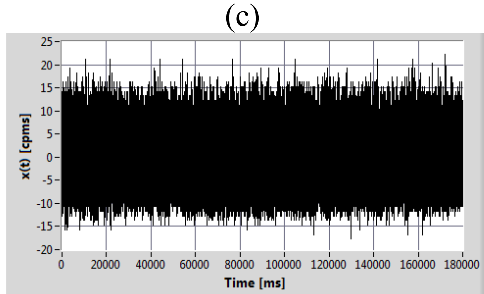

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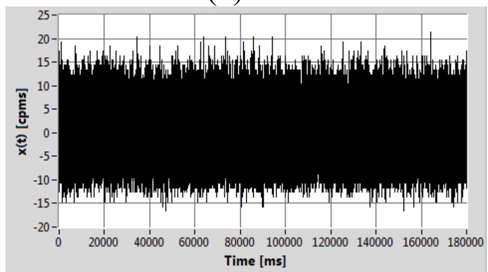



Figure 4. Time waveforms of signal x(t) in the experiments: (a) LIQ1, (b) LIQ4, (c) LIQ7, (d) LIQ10

## III. Analysis of Signals using Autocorrelation Function

Autocorrelation function can be calculated using equation [14, 15]:

$$R_x(\tau) = \frac{1}{T}\int_0^T x(t)\cdot x(t+\tau)dt \tag{1}$$

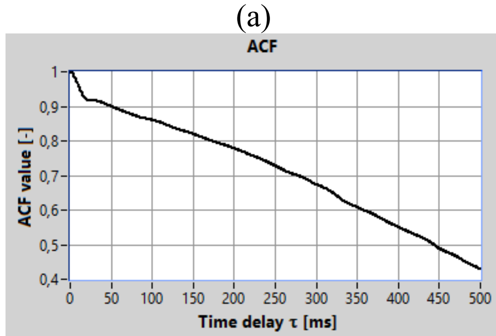
where: $\tau$ – time delay, $T$ – averaging time.

Normalized ACF is defined as follows:

$$\rho_x(\tau) = R_x(\tau)/R_x(0) \tag{2}$$

Normalized ACF waveforms for the discussed types of flows are presented in Fig. 5.

(a)

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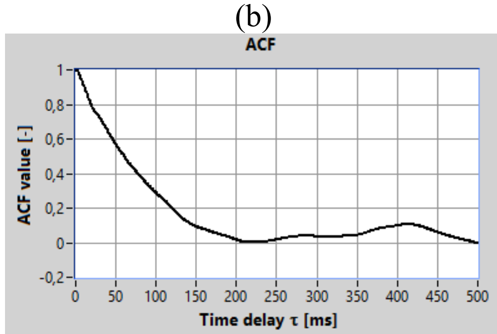
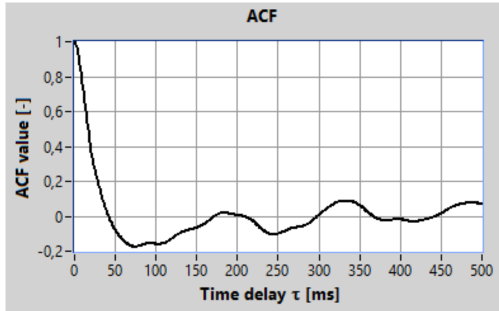



(c)

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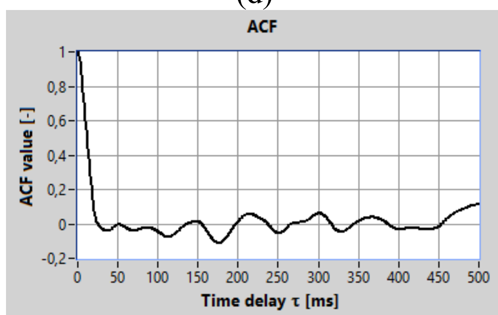



Figure 5. Autocorrelation functions of signal $x(t)$ in the experiments: (a) LIQ1 (slug flow), (b) LIQ4 (plug flow), (c) LIQ7 (transitional plug – bubble flow), (d) LIQ10 (bubble flow).

As can be seen from Fig. 5, the autocorrelation courses for the analyzed types of flows differ significantly. Therefore, one of the following ACF parameters can be used to identify the flow regime:

- ACF value for a given time delay $\tau_g$,
- time delay value for a specific ACF value,
- the area under the ACF graph for the selected time delay range.

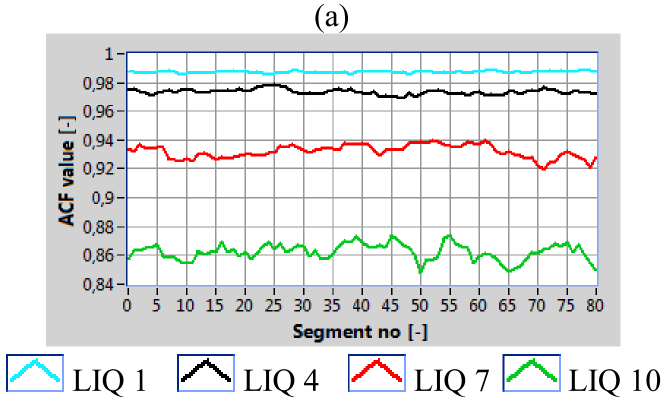
The conducted experiments show that desirable effects are obtained using the ACF value for a given time delay $\tau_g$.

Because the recognition of the flow regime using machine learning methods requires a large set of values for the selected parameter, the following procedure was proposed:

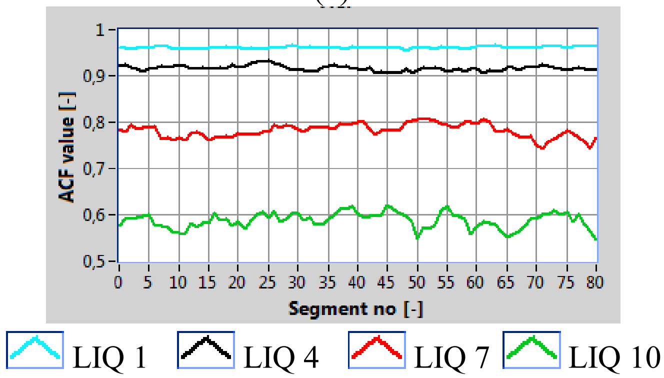
- division of recorded signals into overlapping segments with the number of samples 10,000 (overlapping 80%)
- signal smoothing using a moving average,
- for each segment, the ACF value was determined for different time delay values $\tau_g$.

The obtained results are shown in Fig. 6 for selected values of the delay time $\tau_g$.

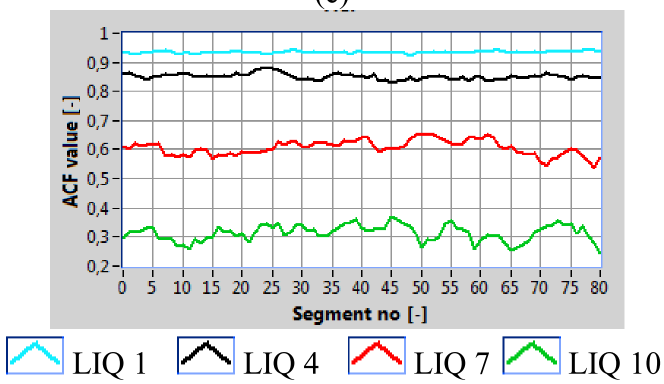
(a)



(b)


1
0,9
0,8
0,7
0,6
0,5
ACF value [-]
0 5 10 15 20 25 30 35 40 45 50 55 60 65 70 75 80
Segment no [-]
LIQ 1
LIQ 4
LIQ 7
LIQ 10

(c)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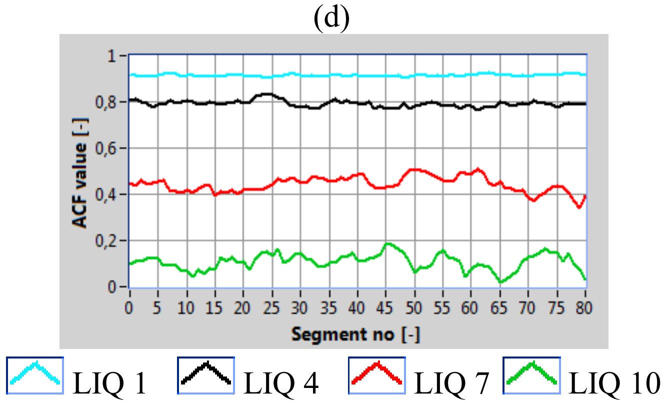
Segment no [-]
LIQ 1
LIQ 4
LIQ 7
LIQ 10

(d)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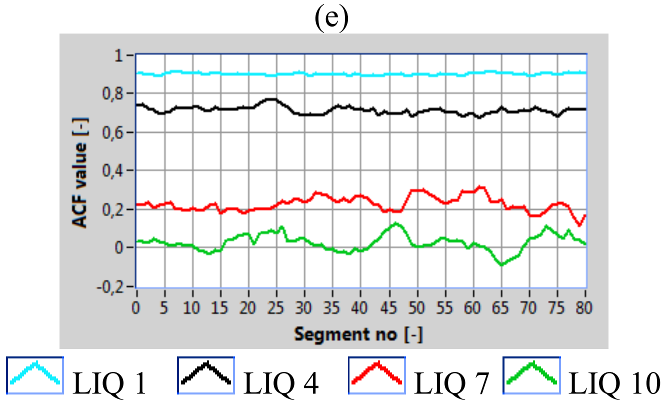
LIQ 1
LIQ 4
LIQ 7
LIQ 10

(e)


1
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ACF value [-]
0 5 10 15 20 25 30 35 40 45 50 55 60 65 70 75 80
Segment no [-]
LIQ 1
LIQ 4
LIQ 7
LIQ 10

(f)

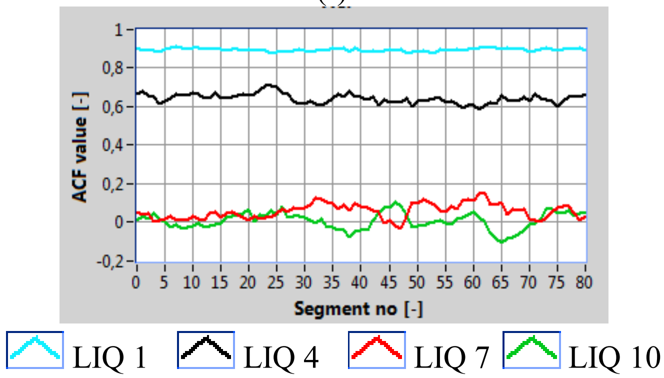


Figure 6. Changes in the normalized value of ACF $\rho_x(\tau_g)$ as a function of segment number for different values of time delay: a) $\tau_g$ = 5 ms, b) $\tau_g$ = 10 ms, c) $\tau_g$ = 15 ms, d) $\tau_g$ = 20 ms, e) $\tau_g$ = 30 ms, f) $\tau_g$ = 40 ms.

Comparing the obtained results leads to the conclusion that the choice of $\tau_g$ value below 30 ms allows to distinguish the flow regime clearly. It has been found that the optimal time delay $\tau_g$ value selection is in the range of 15-20 ms.

## IV. Conlusion

In this work, the signals registered from NaI(Tl) scintillation probe for four regimes of water-air flow as slug, plug, bubble, and transitional plug-bubble in the horizontal pipe were analyzed by use the autocorrelation function. It has been found that for the analyzed in this study the types of flow, the normalized ACF significantly differ. Based on the analysis of the course of normalized autocorrelation functions, the parameters were chosen which are specific to particular flow types.

It has been estimated that the best parameter is ACF value for a given time delay $\tau_g$, and the optimal $\tau_g$ values are in the range 15-20 ms.

In the authors' opinion, the amplitude of the normalized ACF for the selected time delay can be used as one of the parameters for recognition of the water-air flow structure using computational intelligence methods.

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