Evaluate the next nanobubble movement with artificial intelligence

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***Abstract*– This research supports solving the problem of how to know the next movement of the nanobubble, for this purpose, two methods will be used to represent the behavior of air nanobubbles in liquids, such as the correlation of data expressed in an equation and the backpropagation in learning your route. To obtain the positions of the movements of the air nanobubbles at a scale of 10-9 m in diameter, algorithms based on computer vision, using high-power cameras. The correlation of data was identified to generate the equation and the neural network to learn its movements. In conclusion, the behavior of nanobubbles in water was identified, generating a specific movement pattern of $y = 9E\text{-}06x^3 - 0.0034x^2 + 1.6831x + 299.25$; with a correlation of: $R^2 = 0.9976$ managing to obtain a 98.94% certainty, and it was possible to learn these movements by generating the appropriate synaptic weights with a 99.6% certainty in prediction their route or next path.**

***Keywords*-- path, air nanobubbles, predict, digital image processing, backpropagation.**

I. Introduction

Nanobubbles have taken an important role in research, in a variety of fields such as engineering, agriculture, the environment, food, medicine, and industry, among other areas. In the field of energy [1], it reviews the effect of nanobubbles in the process of natural gas hydrates as a large potential energy reserve. Also [2] in his research shows that ozone-pressure water nanobubbles left clean of non-aqueous solutions of trichloroethene (TCE) as residual element, achieving from 0.44% to 7.6% of TCE, concluding that a specific parameter pertinent to the area Interfacial NAPL-water (Non-Aqueous Phase Liquid in water) in the sherwood number had to be modified to satisfactorily describe the TCE solution, in the presence of nanobubble in water. Also [3] applies the oxygen nanobubbles in sodium chloride to analyze the variation in size, concentration and pH degree, at variable temperature to the liquid, concluding in his research that through the semiquantitative process it was possible to establish the level of aggregation and stability of the nanobubble in question of size, implying that being in a range of 1000 to 2000 nm, the pH level is not considered. In another area [4], he mentions that by treating nanobubbles in mud with high solid content and low organic content, varying the DOM (Dissolved organic material), they managed to improve the amount of acidogenic hydrolytic microbes efficiently, producing the maximum of VFA (volatile fatty acid).

This field has shown strong potential and is reflected in published books and articles, such as [5, 6, 7] where it mentions that microbubbles and nanobubbles have several characteristics that are comparable to millimeter and centimeter bubbles, these characteristics are its small size, which results from its size, high bioactivity, low lifting speed, decreased friction, high internal pressure, high gas dissolving capacity, negatively charged surface and the ability to be crushed to form free radicals. Microbubbles have been used successfully in aquaculture in Hiroshima, scallops in Hokkaido, and pearls in Mie Prefecture, Japan, among other places where it presents its potential as a new technology that can be used globally.

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The book published by [8] mentions that sludge bubble column reactors are used intensively as a multiphase reactor in the chemical, biochemical and petrochemical industries to carry out mass transfer operations and reactions in which a gas (compound by one or more reactive components) comes into contact or reacts with a liquid. This volume describes the hydrodynamics of the three-phase gas-liquid-solid flow in a downflow mud bubble column, for this it is necessary to know the multiphasic behavior in which they interact with gases for research and development.

Therefore, knowing the different areas of application of nanobubbles, an important contribution is to know the behavior of air nanobubbles in liquids to have a certainty of the action to be applied, and its possible results.

The method to find the equation that represents the motion of the nanobubble of air in liquid, it is based on tracking the nanobubble (using computer vision), and that path generate a trajectory represented in a third-degree equation. From the trajectory already found, it can be used as input to the learning process of your movement using an artificial neural network backpropagation, so predict the next move. Therefore it is important to use computer vision algorithms to detect the nanobubbles in a video image.

II. AIR NANOBUBBLES

According to [9] they are those fine bubbles of nano-micro size (10^{-9} m) that are formed when air enters the water; air is ground and mixed by high pressure and high speed gear mixing method.

Stay in the water. once the micro-nano bubbles are injected into the water, they will rise much more slowly through the water column compared to the bubbles in conventional air injection systems or with paddle aerators. With what has been said so far we can understand that its application is recommendable and profitable.

III. PREDICCIÓN

According to [10] for prediction, "it is necessary to start from the principle of the regularity and interconnection of the phenomena of nature and society, which allows passing from the description (which basically refers to empirical facts) to other levels of science ", said data can be taken as the starting source, as shown in Fig 1.

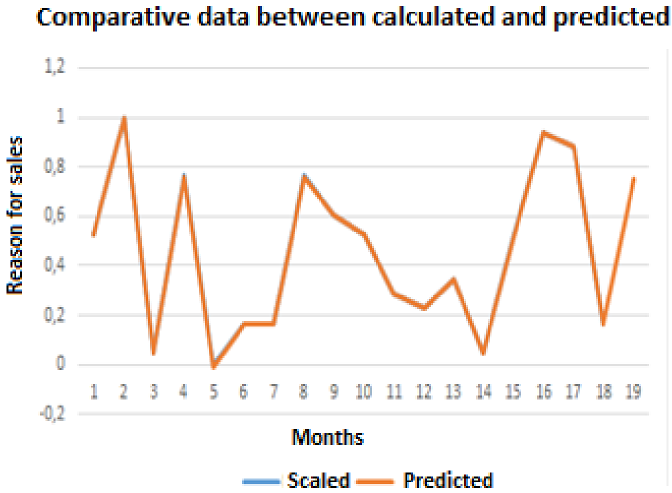

Fig 1: Example of initial data for prediction in time series

IV. BEHAVIOR

According to [11] it refers to "observable and measurable responses or actions". It can be analyzed and represented in equations based on its time evolution represented in an equation with a variable x as a function of time, as seen in the equation:

$$\dot{x} = f(x,t) \tag{1}$$

Where:
$f: D \; C \; R^n \times R \rightarrow R^n$

x: dates of median

t : time

V. ARTIFICIAL INTELLIGENCE

According to [12] states that artificial intelligence "poses complex challenges, ranging from confidence problems, including security risks, to concerns about increasing inequalities, to the disturbing impact of AI on employment" , for [13] "the importance of AI is demonstrated by the impact that its applications have already had in use", also for [14] "One of the most desired characteristics of AI (artificial intelligence) is the ability to take complex decisions ", on the other hand [15]" artificial intelligence (AI) or computational intelligence is the simulation of human intelligence processes by machines. These processes include those capable of learning, reasoning, and improving on their own." Also [16] mentions that "it is the ability of machines to use algorithms, learn from data and use what they have learned in decision-making just as a human being would do."

A. Digital Image Processing

According to [17] "Digital image processing has established itself as a fascinating field that is part of daily life.", "Today it is an indispensable tool in applications for industrial control, automatic quality control, robotics, sensors, telecommunications, medicine, geosciences, environmental sciences, etc. "

B. Neural network backpropagation.

For [18] neural networks "Artificial neural networks are nonlinear approximators of how the brain works; therefore, it should not be compared directly with the brain, nor should it confuse the principles on which the functioning of artificial neural networks and the brain are based, nor should we think that neural networks are only based on biological networks; considering that they only very simply emulate the functioning of the human brain". Also [19] mentions "deep learning was developed in part by inspiring us in our understanding of the brain, deep learning models are not brain models. There is no evidence that the brain implements something like the learning mechanisms used in modern deep learning models." [20] also mentions of the Backpropagation neural network that "it is an algorithm for backward error propagation, it uses the error observed in the output of a multilayer neural network to gradually adjust the parameters that define the response of the network to an input given, with the intention of reducing the error made by the network." Neural network backpropagation model for predicting the behavior of the air liquid nanobubble.

VI. DIGITAL IMAGE PROCESSING TO OBTAIN NANOBUBBLE POSITIONS

A. Detection of the nanobubble

Applying digital image processing with the Python programming language, from the OpenCV libraries such as findContour, morphology, dilate, erosion, etc., following a sequence shown in Fig 2. The location of the nanobubble with the data deposition, size, area, radius, etc.

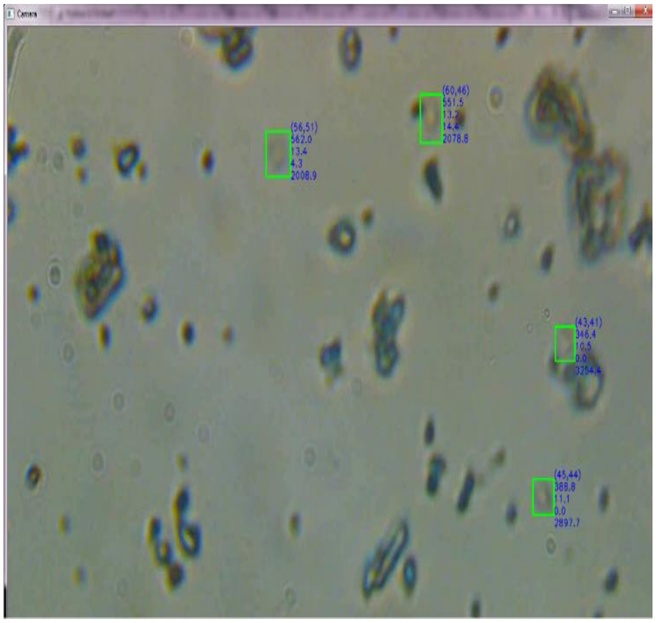

Fig. 2. Location of the liquid air nanobubble

B. Path of the nanobubble

Once located, it is necessary to know the path of each of the air nanobubbles, obtained from Fig 3, and shown in Table I.

A set of sequences of movements of the nanobubble is identified, therefore it is necessary to know the positions of such a sequenc, taking into account that the trajectory sequence is complete.

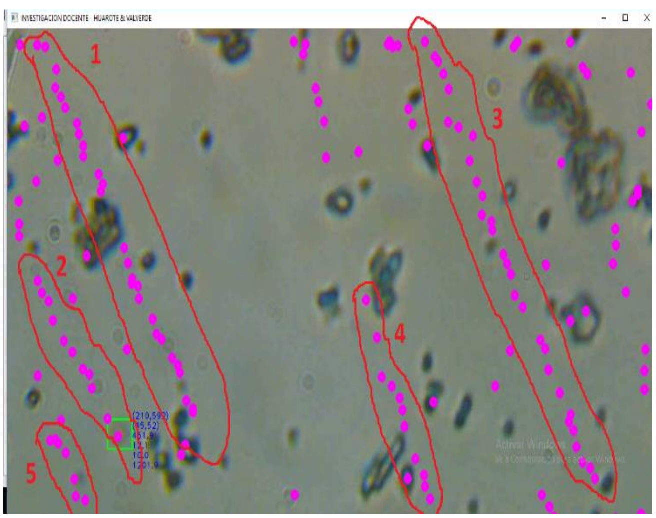

Fig. 3. Path of the air nanobubble in liquid

TABLE I
PATH OF THE AIR NANOBUBBLE

	Path 1		Path 2		Path 3	
N°	**X_1**	**Y_1**	**X_2**	**Y_2**	**X_3**	**Y_3**
1	32	48	36	354	876	16
2	46	54	46	371	880	28
3	74	34	60	386	892	48
4	74	60	72	413	896	68
5	86	76	96	442	902	112
6	96	90	115	464	926	128
7	120	114	148	498	952	144
8	124	132	165	520	946	176
9	136	152	186	564	960	210
10	138	165	210	592	974	232
11	166	194	236	624	976	256
12	176	211	236	644	994	272
13	176	220	250	658	1002	258
14	224	304	262	680	1024	318
15	232	324	**272**	**694**	1030	336
16	248	356			1035	346
17	240	358			1048	383
18	252	366			1060	400
19	256	384			1100	454
20	284	416			1144	533
21	288	440			1165	568
22	298	448			1160	578
23	324	476			1170	592
24	336	488			1180	616
25	340	499			1192	642
26	358	544			1204	648
27	374	560			1216	664

C. Backpropagation for the prediction of the air nanobubble behavior in liquid

The model for predicting the air nanobubble behavior in liquids is given by the structure of the backpropagation neural network of 1 input layers with 2 neurons (additionally 1 bia), 2 hidden layers with 8 neurons for the input to the first hidden layer, 7 neurons for the first hidden layer to the second hidden layer, and one neuron for the output layer. If you want to know a single predicted value, you must necessarily have an output neuron, since you must learn a scaled predicted value according to Table I, of a series of position X. Where the value of X_{n-2} represents the value at a certain position (before X_{n-1}), and the value of X represents the value with respect to the current position. The model to present is shown in Fig 4.

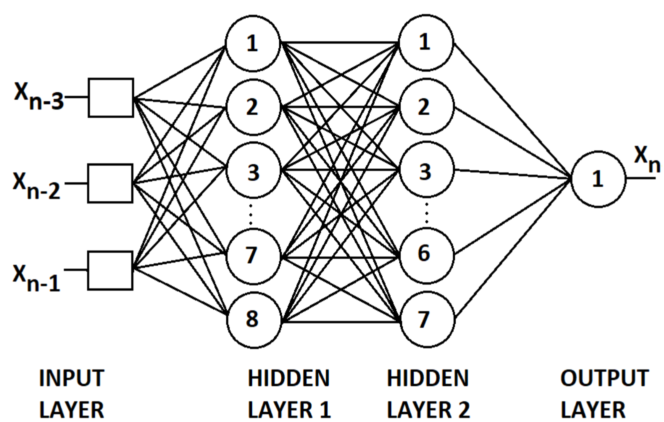

Fig 4: Neural network model proposed backpropagation for prediction

Scale values of the position to a range of [0 to 1] applying the following equations:

TABLE II
EQUATIONS FOR PERFORMING SCALING AND THE REVERSE PROCESS

Equation	**Detail**	**Observation**
$r = \frac{Y - Min}{Max - Min}$	r: scaled value Y: value to scale, Min: Minimum value of the data set Max: maximum of the data set	Required to scale in the range of 0 to 1
$Y = r(Max - Min) + Min$		Necessary to return the original proportion as a function of r

Table II represents the actual values of the positions and scaled values of those positions, is necessary to be able to evaluate the prediction of the next movement of the nanobubble in the video from the historical data set.

The model to be considered for the behavior prediction learning process is a function of path, where X_{n-4} and X_{n-3} will generate X_{n-2}, X_{n-3} and X_{n-2} will generate X_{n-1}, X_{n-2} and X_{n-1} will generate X, considering these antecedents the value of '?' Can be predicted where it represents X_{n+1}. Therefore, for each value of it will represent the input patterns and a respective output as shown in Fig 5.

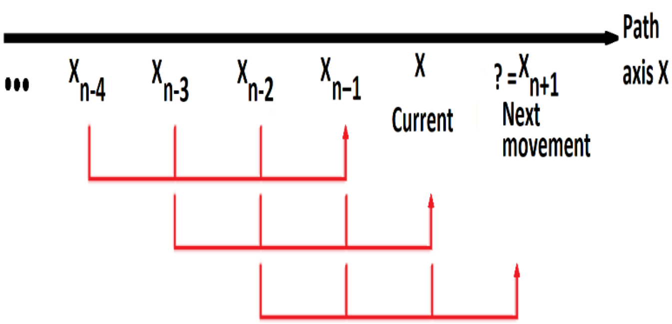

Fig 5: Path for data collection

After having learned path 2 (data 1 to 14 of table 1), after mapping or checking for the position at path X_{n+1} is (x2, y2) = (272,694).

VII. ANALYSIS OF DATA

Based on the data obtained from Table II, the analysis will be performed considering the correlation of data and prediction by backpropagation.

Data mapping

In the Fig. 6, generate the following equation for the path 1: y = -2E-05x^3 + 0,0105x^2 - 0,3488x + 39,255. Con R² = 0,996. In the Fig. 7, for the path 2: y = 9E-06x^3 - 0,0034x^2 + 1,6831x + 299,25; with R² = 0,9976. In the Fig. 8, for the path 3: y = -2E-05x^3 + 0,0105x^2 - 0,3488x + 39,255; with R² = 0,996. For the fig 6, 7 y 8 respectively.

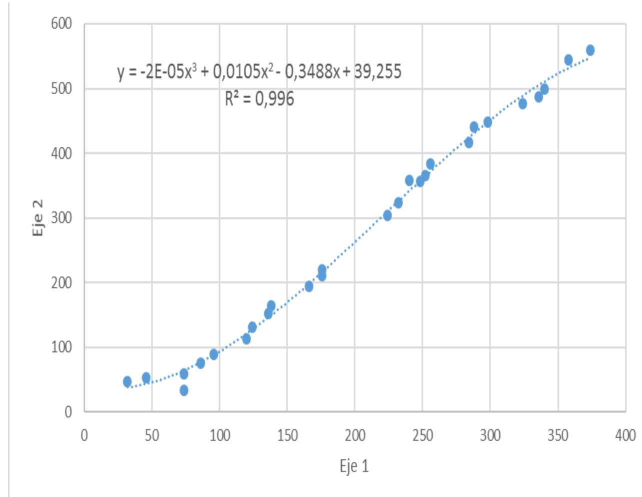

Fig. 6. Location of path 1 of the air nanobubble in liquid

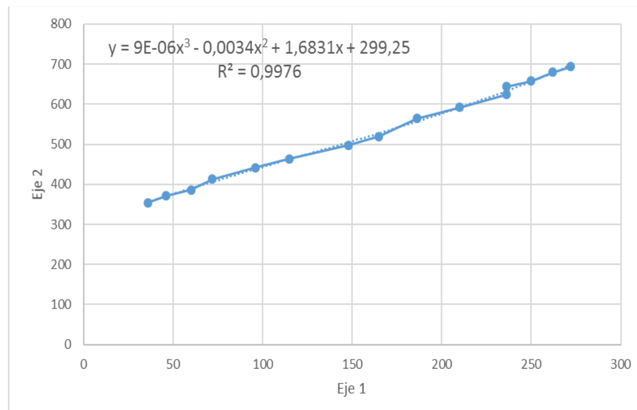

Fig. 7. Location of path 2 of the air nanobubble in liquid

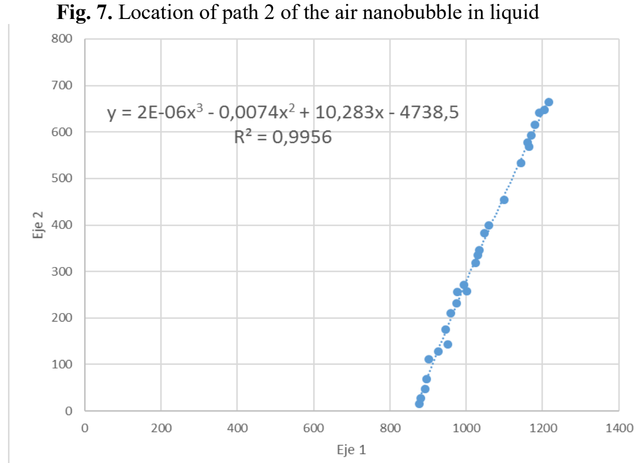

Fig. 8. Location of path 3 of the air nanobubble in liquid

We will consider the equation of the of the nanobubbles behavior of path 2 since it has the closest correlation to 1: y = 9E-06x^3 - 0.0034x^2 + 1.6831x + 299.25. R² = 0.9976. Reason why the equation will be taken that measures the behavior of nanobubbles compared to the other paths.

For the neural network method, the tests were performed giving encouraging results, of the 14 original values (of the positions of each nanobubble) where it is represented in positions, predicted for X + 1, obtaining the results in Table III, where the value predicted for X + 1 is given by 1.03874161938 which represents 692.629768 (obtained by performing the inverse scaling process y = r (Max-Min) + Min) of position.

TABLE III
TESTS PERFORMED ON THE VALUES THAT ARE PART OF THE TRAINING

Position	Original value	Scaled value (SV)	Obtained value (OV)	Error of each value (SV-OV)
X-13	354	0.052147	0.052147	0
X-12	371	0.052147	0.052147	0
X-11	386	0.098159	0.805158502	-0,7069995
X-10	413	0.180981	0.82143915	-0,6404581
X-9	442	0.26993	0.82813	-0,5582
X-8	464	0.33742	0.8479136	-0,5104936
X-7	498	0.44171	0.86957702	-0,4278670
X-6	520	0.50920	0.878212	-0,369012
X-5	564	0.64417	0.898564	-0,254394
X-4	592	0.730061	0.902544	-0,172483
X-3	624	0.828220	0.922214	-0,093994
X-2	644	0.889570	0.929898	-0,040328
X-1	658	0.93251533	0.939794	-0,0072787
X	680	1	0.9448799	0,0551201
X+1	694		1,0387416193	

In the Fig.8 The show two cases to learn and real, comparing the results, both from what we learned, as well as from the actual movement of the nanobubble in function of Table III.

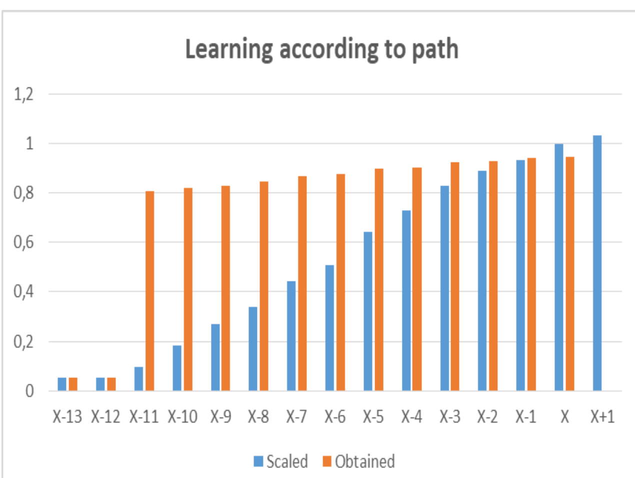

Fig. 8. Comparison of learning with reality

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In the Fig.9 the error obtained when performing the artificial neural network-based learning tests is displayed, comparing the results, both from what we learned, as well as from the actual movement of the nanobubble in function of Table III.

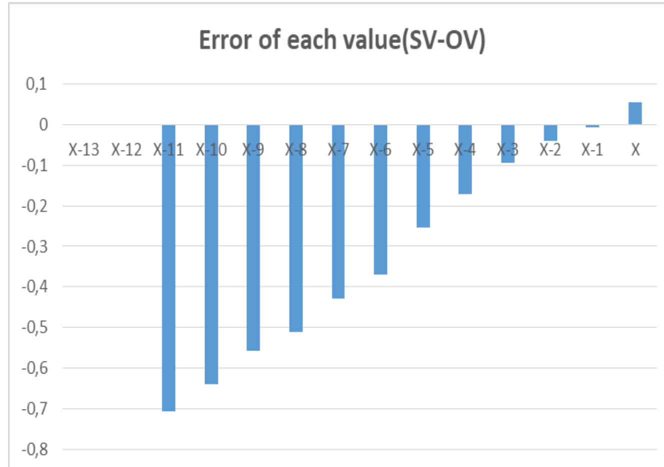

Fig. 9. Error of learn

VIII. CONCLUSIONS

The air nanobubble behavior was determined using digital image processing, such as the position, height, width, area, radius, and color hue for the highlight of the nanobubble.

In the data correlation, the nanobubbles behavior in aqueous medium was determined, which is: $y = 9E\text{-}06x^3 - 0.0034x^2 + 1.6831x + 299.25$; with a correlation of: $R^2 = 0.9976$. Applying the value of x = 272 to the previous equation it was obtained y = 686,620432, which implies an error of 7,37956%, what represents the 98.94% of certainly.

For the prediction method using neural network backpropagation, the results were encouraging, as resulted y = 692,629768, which implies an error of 1,37023%, which represents 99.6% of certainty.

The prediction of the behavior of nanobubbles allows us to predict future chemical reactions in liquids on a nanometric scale, especially ionic ones, to obtain new substances through artificial intelligence.

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