Optimal Kernel Classifier in Mobile Robots for Determining Gases Type

By 16_NLH

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Abstract—: **The use of TGS sensor and Arduino could create a robot to be capable of detecting and classifying some gases. In this research, 3 kinds of SVM Kernel Classifiers are investigated. Robots equipped with 3 TGS sensors are used to classify methanol and acetone. Xbee modul is used as a communication medium between robots and server. The robots are run in the experimental environment. When they detect the gas, they will get closer to the source and classify the gas type. The classified gas data is then sent to the server. From this research, it can concluded that polynomial and RBF have better performance in classifying methanol and acetone.**

Keywords— acetone, methanol, kernel classifier, TGS sensor, SVM.

I. Introduction

Air pollution containing harmful gases that occurs in daily life could give some bad impacts. It can threaten human life and cause some diseases, such as cancer, TBC, etc [1], [2], [3], [4]. The pollution can be caused by some factors, i.e. from nature activities, such as forest fire, volcanic eruption and nature gases, and also from human activities, such as factory process, transportation, and office's activities [5].

The risk that caused by poisonous gases could be reduced by using modern technology. Even though, the gas sometimes has no smell, no color, and cannot be felt by human, the modern technology is capable to know the source and the concentration of some gases. With some improvement methods, modern technology not only could detect but also classify the gas type. Some of those methods are KNN and ANN. However, these methods still have drawbacks, such as the errors still often occurred, still rely on the closer value of classifying and cannot perform well if there is a lacking of data [6]. These drawbacks make the research became hard to be done.

To handle the problems, one solution that could minimalize the errors and make process more efficient is needed. Support Vector Machine method (SVM) is one of solution that can be implemented in this research. SVM is easy to be applied and it could give accurate result. Classification of gas types in this research has aimed to identify the type of existing gas. By knowing the gas type, the existence of harmful gas that is detected by the sensor can be quickly recognized. Thus, the danger that can be caused by this gas can be avoided. This study is also expected to be useful for industries and government in decreasing the negative impacts that can be caused by the ignorance of the poisonous gasses.

In its application, there are a lot of kernels that can be implemented in SVM. Each of them has advantages and disadvantages. To know what type of kernels that has better performance, in this research, 3 types of SVM kernels, namely: linear, Radial Basis Function (RBF), and polynomial were compared and analyzed. By this comparison, it can be known which function is the most reliable among the three functions. Thus, which functions are most suitable for gas classifiers can be determined. The accuracy and speed of the algorithm in classifying gases is one of the measurements that determine the reliability of the algorithm. By having correct kernels, the performance of the SVM can be increased.

II. Support Vector Machine

The classification of gases is needed to determine the individual compound of complex mixture (quantitative information). Although some sensors are good in detecting and identifying compounds (qualitative measurements), but they are not good in giving quantitative information of individual compound of complex mixture [7]. Learning machines can be used to enhance the performance of sensors so that they can be used as good classifiers. In choosing proper learning machines that can be used in gas classification, some conditions should be considered, such as: 1) How fast the rate of convergence of the learning process can be achieved is; 2) How to control the rate of convergence of the learning process is. The shorter time to reach convergences, the shorter time to classify the gas type is. The shortest time of classifying the gas type is needed in order to save human life. It can be imagined, if the gas sources (especially gas that contains the poisonous substances) are slow to find, of course more victims will occur. This threat was described by H. Ishida [8].

The classification of gas substances can be conducted using NN. However, NN has some drawbacks, such as: NN needs more time in order to get convergences. This limitation can be accomplished by using SVM. In SVM, the convergences can be got more quickly than NN. It is due to the data that should be generated will be divided into some parts by the SVM. It can separate the datasets by searching for an optimal separating hyper-plane between them [9].

Moreover, SVM can work using a restricted amount of training data. By exploiting optimal hyper-plane, the largest distance or margin from the separating hyper-plane to the closest training vector can be provided. The maximizing of that linear discriminant margin can minimize the generalization errors. Thus, better generalization with high probability can be got [10]. These facts are contradictive with NN that cannot run well using a limited training data. Therefore, SVM are widely used in overcoming pattern recognizing problems [11]–[15]. The success of SVM application has been proved by Marcela [16] who compared 3 classification techniques, i.e. 1. Statistical Classifier (LDA); 2. Multi Layer Perceptron (MLP) using NN; and 3. Support Vector Machine (SVM). Marcela stated that SVM was better than two other classification techniques. Weizhen Lu also stated that SVM was better than NN in [17]. There were three reasons introduced by Weizhen in order to state SVM power, such as: i) it contains less number of free parameters than the conventional NN models; ii) SVM method provides better predicting results than neural network does; iii) the typical drawbacks of neural network models, e.g., "over-fitting" training and local minima, can be eliminated in SVM method [17].

The operating the SVM algorithm, a kernel is usually used. It has function to transform the input data space to the required form. A kernel trick is a technique that is generally implemented in SVM. Basically, that kernel takes a low-dimensional input space and transforms it into a higher dimensional space [18]. The kernel can help in converting a non-separable case to separable case by adding more dimensions to it. It is very useful for getting a more accurate result.

III. EXPERIMENTAL SET-UP

For the accuracy precision of robot, the mechanical design must be paid attention. The robot has some important part, such as: acrylic and spacer. The use of 3mm thick acrylic is aimed to sustain and set the component layout, so that the robot looks neater. The use of spacer has purpose to sustain parts of each floor of robot. In this research, the first floor of the robot contains some components, such as: motor driver L298 D, ubec converter, and 12 v battery. In the second floor, there are arduino mega 2560, raspberry pi3, and ultrasonic HCSR 04. Meanwhile, in the third floor position, there are: compass, xbee module, TGS Sensors. In the top floor, there are LCD and switch to make the robot operation easier to be operated.

A. *Diagram Block*

The diagram in Fig 1 outlines the working principle of the robot. The robot uses 2 types of inputs, i.e. the first input is distance sensor that has function to avoid obstacles and the second input is TGS sensor that is processed by microcontroller until it generates an output, i.e. motor and LCD.

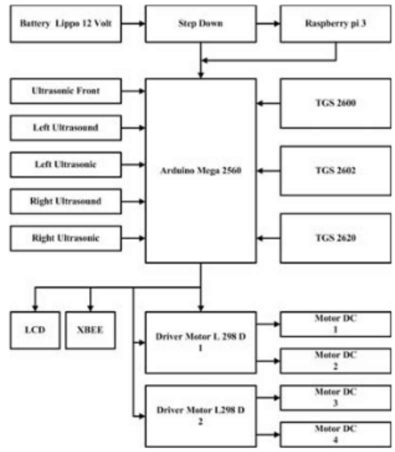

Fig 1. Diagram Block of Robot

B. *Flowchart*

The process of classifying the gas was started when the system was activated and initialized. Ultrasonic sensor would detect the distance around it. The obtained information was then inputted to the microcontroller so that it could control the robot's movement for finding and detecting the gas source. If the robot does not find the gas source, the process of finding the gas source will be continued until the process done. When the robot detected the gas source, it will classify the gas using SVM method. Fig 2 shows the robot flowchart.

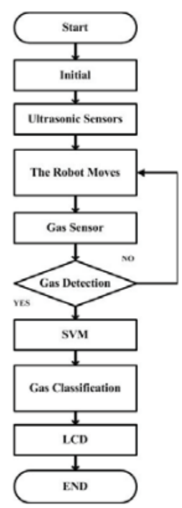

Fig 2. *Flowchart* of robot

C. *SVM Code*

The data training and testing process can be seen in our previous work [19]. The pseudocode for the 3 types of kernels, i.e. Linear, RBF and Polynomial is shown in Fig. 3.

```
            }
            results[j] = (Qfloat) (gamma*chi2);
        }
        if( vcount > 0 )
            exp( R, R );
    }

    void calc( int vcount, int var_count, const float* vecs,
               const float* another, Qfloat* results ) CV_OVERRIDE
    {
        switch( params.kernelType )
        {
        case SVM::LINEAR:
            calc_linear(vcount, var_count, vecs, another, results);
            break;
        case SVM::RBF:
            calc_rbf(vcount, var_count, vecs, another, results);
            break;
        case SVM::POLY:
            calc_poly(vcount, var_count, vecs, another, results);
```

Fig 3. SVM code

The pseudocode

IV. Result and Discussion

This study was conducted using SVM method with 3 types of kernels, i.e. linear, polynomial, and RBF. 2 types of gases (methanol and acetone) were used in this experiment. The robots were set to run in the experimental arena with different starting points with the distance of 0.5 m until 2,0 m. Each of distance was divided into three sub starting position, i.e. left, middle, and right. The data obtained from the experiment were presented in Table II – Table IV.

TABLE I. Right Starting Position

Distance (m)	Gas source	Gas detected	Time in classifying gas (s)		
			Linear	Polynomial	RBF
0.5	Methanol	Methanol	164	10	79
	Acetone	Acetone	32	31	18
1	Methanol	Methanol	20	21	11
	Acetone	Acetone	22	41	16
1.5	Methanol	Methanol	13	19	4
	Acetone	Acetone	31	54	5
2	Methanol	Methanol	17	14	5
	Acetone	Acetone	28	17	42

From Table II, where the starting position of robot was set on the right position, it can be seen that the fastest kernel in classifying methanol and acetone was kernel RBF with 4 s and 5 s respectively (in 1,5 meter distance). RBF can also classifying faster than the other kernel in 2.0 m distance. It can recognize the gas source of methanol and acetone quickly.

For left starting position, the fastest kernel in classifying the methanol and acetone gas was polynomial kernel with time 9 s and 13 s respectively (in 2 meters distance).

From table IV, middle starting position, it can be seen that the fastest kernel in classifying methanol was poly and RBF kernel (with 1.5 m distance and 2 m respectively), while for classifying acetone, the polynomial was faster than the other kernel (22 s in 0.5 m distance).

TABLE II. Left Starting Position

Distance (m)	Gas source	Gas detected	Time in classifying gas (s)		
			Linear	Polynomial	RBF
0.5	Methanol	Methanol	38	34	22
	Acetone	Acetone	54	27	40
1	Methanol	Methanol	38	120	30
	Acetone	Acetone	34	53	26
1.5	Methanol	Methanol	16	61	11
	Acetone	Acetone	30	27	33
2	Methanol	Methanol	54	9	28
	Acetone	Acetone	26	20	13

TABLE III. Middle Starting Position

Distance (m)	Gas source	Gas detected	Time in classifying gas (s)		
			Linear	Polynomial	RBF
0.5	Methanol	Methanol	51	57	22
	Acetone	Acetone	29	22	24
1	Methanol	Methanol	85	40	11
	Acetone	Acetone	45	31	26
1.5	Methanol	Methanol	26	1	8
	Acetone	Acetone	30	36	27
2	Methanol	Methanol	7	23	1
	Acetone	Acetone	26	34	23

The accuracy of classifying of gas experiment (methanol and acetone) using 3 types of kernel was 100%. It means that the gas can be classified exactly with 0% error. From the obtained data in Table II – Table IV, it can be concluded that the poly kernel is the fastest in classifying the f methanol gases, while RBF kernel was the fastest in classifying the acetone of gas.

V. Conclusion

In implementing this research, there were some difficulties occurred, such as the disturbance of weather or environment that can influence the success in classifying the types of gases. However, in this research, the environment was set as real as possible. From this research, it can be concluded that there are two fastest types of kernels in classifying the methanol and acetone, i.e. polynomial and RBF. The polynomial is the fastest kernels in classifying methanol while RBF is the fastest kernel types in classifying acetone. The linear kernel is the longest one in classifying the gases. However, although they have different time duration, the 3 types of kernels have 100% accuracy.

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