A new optimization algorithm for image classification based on the Support Vector Machine

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Abstract— Today, with the aim of improving cross-border security, one of the technologies that today many countries are thinking to apply is WMSN. Applying this technology enables gathering information about potential activities along the border through captured images. This will make it easier for security authorities to detect and identify illegal activities along the green borderline. However, images captured by multimedia sensors can often contain information that aren't with interest for state security authorities.

In this paper we will present an algorithm that will enable the classification and identification of images captured by multimedia sensors. The captured images will be sent through the network to the security authorities at the monitoring center, and after the classification are sent to border patrols. The working principle of this algorithm is based on the Suport Vector Machine (SVM).

Keywords—algorithm, borderline, images, security, SVM WMSN.

I. Introduction

State border security is a very important factor of every country. In particular, green borderline. Today for this purpose systems and different technology are applied. One of the most advanced technologies is the application of wireless multimedia sensor networks (WMSN). This technology is applied along the green borderline with areas that are characterized by steep terrains and covered with high forests, for more you can read in [1].

As was discussed in [2], the challenge of this technology is to saving more energy. Therefore, activation of the sensor nodes will be made only in those cases when there is motion in such areas that cover multimedia node. In order to saving more electricity, sensor nodes in most of the time will stay in the inactive state.

The images captured by WMSN located along the green borderline must be processed by the network devices and sent to the security central monitoring centre for analysis of information [3]. A monitoring centre is shown in Figure 1.

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From the monitoring centre as shown in Figure 1, border security authorities realize continuous monitoring of the borderline "in press" [4].

In other words, the main tasks of the monitoring centre are:

1) Continuous observation of the borderline and identification of suspicious activities
2) Receiving alarms from security systems placed along the border and made their analysis on the optimum time, so that appropriate measures can be taken by the security authorities, depending on the degree of risk;
3) Maintaining of equipment located along the green borderline;
4) Communication and coordination of works with border patrols;
5) Information regarding on going border patrols in terrain with new information about the events on the border line, etc.

Fig. 1. Centre for borderline monitoring

In those border areas, where is located high resolution technology, images are direct. However, in border areas sensor nodes are placed, the images will appear only in those cases where there is an area covered by sensor nodes. However, it should be signified that along the green borderline there can be movement of wild animals and birds. So that images captured by the sensor nodes, often contain irrelevant information for security authorities "in press" [4].. The objective of this paper is to introduce a new algorithm which will be able to classify and automatically identify humans from animals.

In this paper, we will identify the problem, and then, we will examine briefly the working principle of support learning machines. In the fifth section we will present the steps through which passes the proposed algorithm. In the end we will discuss and present the results obtained.

II. PROBLEM FORMULATION

Power supply of sensor nodes is vital to the operation of WMSNs. In other words, energy is WMSN lifetime itself. The sensor nodes located along the borderline, with the aim of saving energy, most of the time, need to stay asleep. Activation of the sensor node, occur only after it has detected a movement in the area covered by the sensor node. However, it should be noted that along the green borderline can be movement of animals, birds, criminal groups, etc. The images captured by the WMSN, routing through the network to the nearest police station, and then to the security central monitoring centre [5] for analyzation. Border security officers, currently during most of the times need to stay in front of the monitor for monitoring security devices placed along the green borderline. Such monitoring of security equipment's located along the green borderline is usually troublesome for border security officers. This monitoring method is not very efficient because as a result of fatigue or carelessness of security authorities, any mistake can be done during the monitoring. It could occur that there may be any illegal activity along the border and not be noticed by the security authorities.

To solve this problem in the following we will present a new algorithm based on support vector machine. This algorithm will enable an automatic identification and classification of images captured by the multimedia sensor nodes. In other words, this algorithm will enable the identification of the cases when criminal groups have crossed along the borderline and of the cases when animals have crossed or any movement of any bird. This algorithm will provide a very suitable solution for border security officers by enabling them that automatically of receive an alert (image) if occur any activity along the green borderline.

III. SUPPORT VECTOR MACHINE

The SVM is based on theoretical learning theory developed by *Vapnik*. SVM are learning machines based on statistical learning theory that can be used for pattern classification or regression. They provide high generalization performance without the need to add a priori knowledge, even when the dimension of the input space is very high. Current SVM is sensitive to noise and outliers because SVM assumes all data points have the same importance in classification problems [6], [11]. In training the SVM, an *n*-class problem is converted into *n* two-class problems. For each two-class problem, the decision function that maximizes the generalization ability is determined [7]. Data set classification by SVM is realized looking borders with maximum margin of separation between data trained in a space (called a kernel space) obtained by a transformation function. The maximum difference in general usually reduces the error [9]. In other words, SVM classifies data by finding the best hyperplane that separates all data points of one class from those of the other class. Then, for each class, we score each feature vector extracted using the SVM trained for that class [8], [10]. It should be noted that maximizing the distance between classes will help us to decide on the right hyper-plane. This distance is called as Margin. An example of such separation is shown in Figure 2.

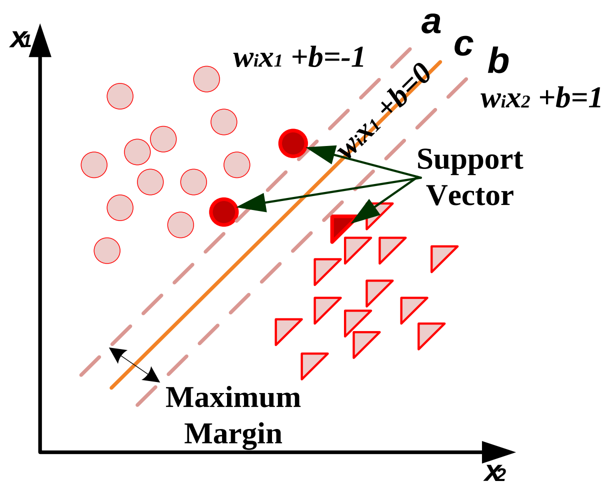

Fig. 2. Optimal Separating Hyper-plane

In Figure 2, we have presented three hyper-planes, respectively the hyperplane a, b, and c. From Figure 2, it can be seen that the margin for hyper-plan c is significantly higher compared with hyper-planes a and b. Therefore, in this case the right hyper-plane is hyper-plane c "in press" [4].. Also, another reason why we should selecting the hyper- lan with a higher margin is robustness. If we decide for a hyper-plan that has a low margin then in this case there is more probability to mistake during classification. Figure 3 shows such a case.

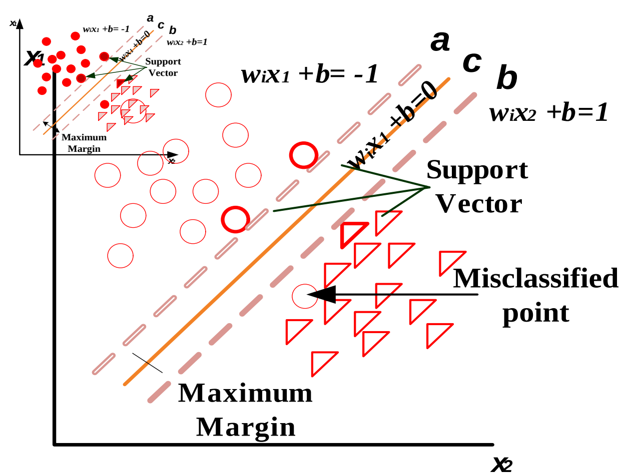

Fig. 3. Case of the misclassified data

From Figure 3 it can be seen that one of the data that belongs to hyper-plan a (a circle), located at the data belonging hyper-plan b. In this case, the SVM has a feature that allows ignore the data belonging to the hyper-plan ***a*** and located in the hyper-plan ***b*** and find the hyper-plane that has maximum margin. However, in this case we should also consider the probability of error that will be discussed in the results sector.

Following is presented briefly the mathematical formulation of the principle SVM.

Let x_i *be* a vector with *n* elements, where ***i*** take values *i*ϵ*(1....n)*, while $w_{1,j}$ a vector with weights of neurons that respond the input vector values. Where *j* take values *j*ϵ*(1...n)*.

In Figure 4, is presented the network architecture which defines the input neurons and their weights.

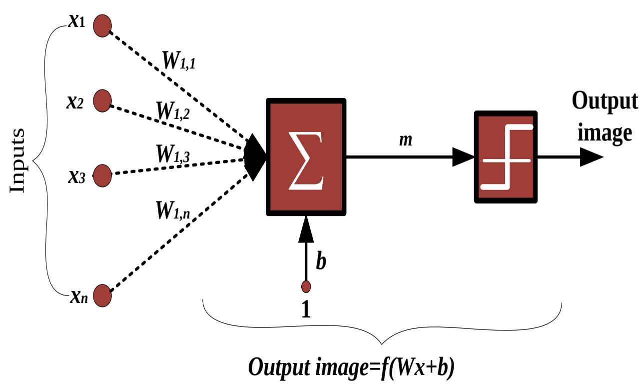

Fig. 4. The architecture of the Network

In the output, individual element inputs x_i are multiplied by weights $w_{1,i}$. This is given by the expression

$$m = \sum_{i}^{n} \left(w_{1,i} x_i + b \right) \tag{1}$$

Where ***xi*** are values of the vector, whereas $\boldsymbol{w_{1,i}}$ are input weights of neurons. The neuron has a bias *b*, which is summed with the weighted inputs to form the net input *m*. This sum, *m*, is the argument of the transfer function *f* a Single-neuron perceptron can classify input vectors into two categories as in expression (2):

$$f(m) = \begin{cases} +1, if\ m \geq 0 \\ -1, if\ m < 0 \end{cases} \tag{2}$$

In Figure 5 is shown a schematic form of the transfer function.

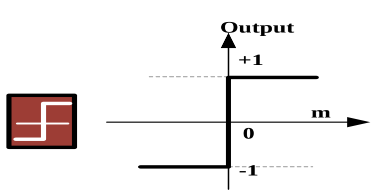

Fig. 5. Symmetric hard limit transfer function

Now finding the outputs for each of the transfer functions. The output of the network is given by:

$$Output=hardlims(m) \tag{3}$$

Therefore, if the inner product of the weight matrix (a single row vector in this case) with the input vector is greater than or equal 0, the output will be 1 “in press” [4]. If the inner product of the weight vector and the input is less than 0, the output will be -1. We conclude from this that the transfer function divides the input space into two parts, namely in the positive and in the negative part.

IV. THE PROPOSED ALGORITHM

In this section we will present a new algorithm that will enable the classification of different groups of images. The working principle of this algorithm is based on SVM.

This algorithm can be summarized as follows. Let's take an image *A(i,j)* as the input image with dimensions *mxn*. Where ***i*** takes values *i*ϵ*(1....m)* and ***j*** take values *j*ϵ*(1...n)*. This image will be compared with 50 images *B (l, k)* for each category. Where ***l*** takes values *l*ϵ*(1....m)* and ***j*** take values *k*ϵ*(1...n)*. In other words, this algorithm goes through several steps, which are presented as follows.

Algorithm: The algorithm goes through these steps:	
Step1.	*Read input colours image A(i,j) from WMSN (in the our case is the Lena image);*
Step2.	*Give the path where is located the folder with files in which are located the separate groups of images;*
Step3.	*Read fullfile in given path;*
Step4.	*Set define the data for each category of images and read all images in the files;*
Step5.	*Use partition method to trim the set;*
Step6.	*Training data from four image sets;*
Step7.	*Define the features of training data for four image sets;*
Step8.	*Classification of images categories;*
Step9.	*Compute average accuracy;*
Step10.	*Comparison input image with other categories of images;*
Step11.	*Display the string label (Id)**;***
Step12.	*Identification Id label;*
Step13.	*Is Id label equal with Category 1, 2, 3 or 4;*
Step14.	*If is true, then display category identification.*
Step15.	*If output is human (Id = 4) then send an alert to the border patrol.*

V. RESULTS AND DISCUSES

In this section we will present and discuss the results achieved with the application of the new algorithm proposed by us for two different test cases. Results are derived by using the MATLAB 2016a and several different sets of images taken from the Internet. Used images have different dimensions and pixels from each other.

In the first case we have taken for testing four different categories of images, such as wild animals, poultries, domestic animals and humans. These images represent the categories that are among the most possible categories to be present along the green border. However, we should note that our proposed algorithm, the same works for the largest number of categories of images.

Images are classified into a folder with four different files. In the first category we have classified (set) images of wild animals. Wild animals are one of the most frequent categories that can pass from one side to the other side of the border. In the second category we have classified (set) images of the birds, which can also be very active along the borderline, where are located multimedia sensor nodes. In the third category we have classified (set) images of domestic animals. Domestic animals are often the target by criminal groups. In the fourth category we have classified (set) images of human. The fourth category of images is one of the main categories from which occurring all the illegal activities along the green borderline.

In other words, criminal groups are those that the border security authorities tend to keep under surveillance, so that their illegal activity along the green borderline can be prevented. In Figure 6, it is presented complete workflow of the proposed algorithm.

Initially, algorithm will test four groups of images for find the features for each category of images.

Creating Features from 4 image sets

- Image set 1: Deer.
- Image set 2: Birds.
- Image set 3: Cows.
- Image set 4: Human.

After that are features extracted for the four groups of images, the algorithm will make training images by category, in order to realize their classification with input image category.

Training an image category classifier for 4 categories.

- Category 1: Deer
- Category 2: Birds
- Category 3: Cows
- Category 4: Human

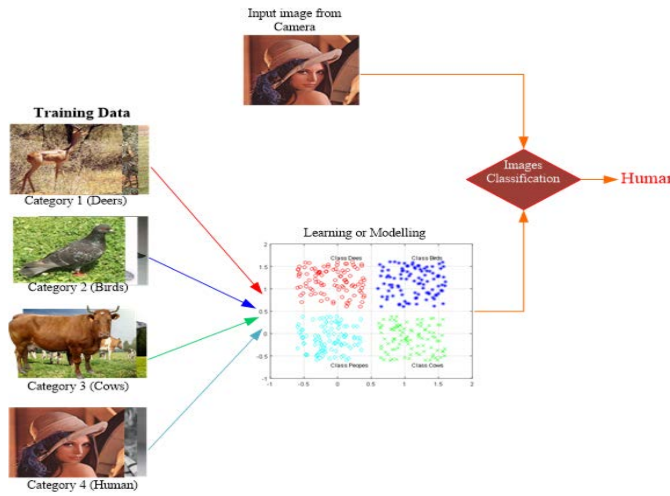

Fig. 6. Workflow structure of the proposed algorithm

After classification groups, training and evaluation of each category of images is realized. When completed evaluation of all groups involved in testing, the input image is compared with each of the categories of trained images. As the result of the application of the proposed algorithm, each image coming from the sensor nodes located along the green borderline to the monitoring centre automatically will be classified that the which category of images it belongs. In other words if the image captured by the sensor node is a deer, then the algorithm, after training will classify as deer, if the image captured is Bird will classify as Bird, etc. In this case, as input image for testing, we have taken the image of Lena. This image is compared with each of the four categories of images in the database, and after comparison, as shown in the table, the algorithm in output presents that the input image is the **human**.

In Table 1 are presented estimated values for each category of images, and a final result is obtained at the output.

TABLE I. PRESENTATION OF VALUES, AFTER TRAINING IMAGES

Known	PREDICTED			
Category	Deer	Birds	Cows	Human
Deer	0.91	0.09	0.00	0.00
Birds	0.04	0.94	0.00	0.02
Cows	0.13	0.09	0.66	0.13
Human	0.00	0.02	0.00	0.98
Average Accuracy is:			0.87	
Output:	Input image is: **Human**			

From the results presented in Table 1 can be seen that with the application of the proposed algorithm, can be realized classification and identification automatically, of every image that comes from any multimedia sensor nodes to the monitoring centre. But in this case, we must also consider the degree of error of the algorithm in the images classification process. The degree of possible error expressed in percentage for the case of grouping of images in four categories is presented in Table 2.

TABLE II. ACCURACY AND ERROR RATE OF THE ALGORITHM FOR THE FIRST CASE

Number of images	Accuracy%	Error %
50	97	3
40	96	4
30	95	5
20	92	8
17	90	10
15	87	13
10	85	15

In Table 2, we have presented the accuracy and error rate of the algorithm in dependence of the number of images used for testing in each category. Also, the accuracy and error rate of the proposed algorithm is presented graphically in Figure 7.

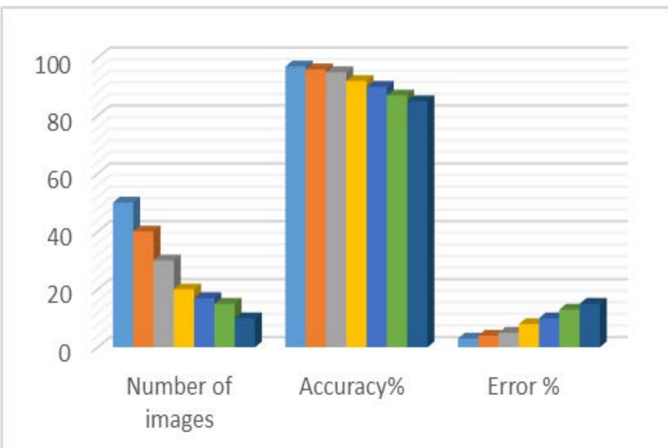

Fig. 7. Graphical display of accuracy and error rate depending on the number of images.

From Figure 7 and Table 2, we can see that if are taken 50 images per test in each category, the accuracy of the algorithm is 97%, respectively the error rate is 3%. If are taken 40 images per category, the accuracy of the algorithm is 96%, respectively the error rate is 4%. If are taken 15 images per category, the accuracy of the algorithm is 87%, respectively the error rate is 13%. If are taken 10 images per category, the accuracy of the algorithm is 85%, respectively the error rate is 15%. In other words, if the number of images per category is greater, the accuracy of the algorithm is greater, respectively the lowest error rate. If the number of images per category is smaller, the accuracy of the algorithm is smaller, respectively the highest error rate. However, it should be noted that the greater the number of images per category, the greater the delays in processing outbound results.

In the second case, we have split the images into two sets. In one set we have included all kinds of images that represent, different animals, poultry, etc. and in the other set we have included images that represent people. In Figure 8 we have presented the grouping of images and workflow of the proposed algorithm.

Fig. 8. Grouping of images and workflow structure for the second case.

From Figure 8, we can see that the image captured by the multimedia sensors will be compared with only two sets of images. Comparing the image captured by WMSN with just two sets of images will directly affect the performance improvement of the algorithm in processing data. Also, in this case will improve the accuracy of the algorithm. The degree of possible error expressed in percentage for the case of grouping of images in two categories is presented in Table 3.

TABLE III. ACCURACY AND ERROR RATE OF THE ALGORITHM FOR THE SECOND CASE

Number of images	Accuracy%	Error %
50	99	1
40	99	1
30	99	1
20	98	2
17	95	5
15	94	6
10	91	9

In Table 3, we have presented the accuracy and error rate of the algorithm in dependence of the number of images used for testing in each category for second case. Also, the accuracy and error rate of the proposed algorithm for second case is presented graphically in Figure 8.

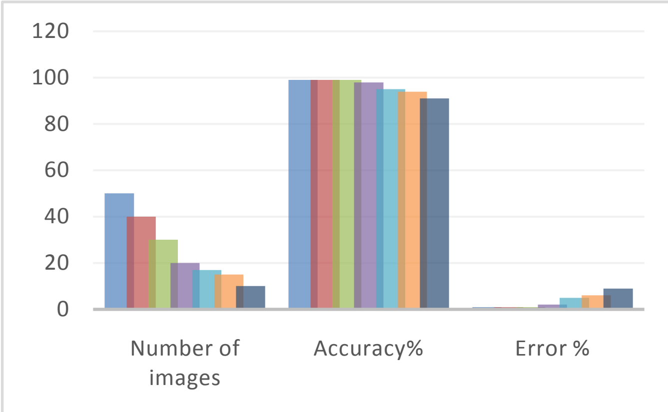

Fig. 8. Graphical display of accuracy and error rate depending on the number of images.

From Figure 8 and Table 3, we can see that if are taken 50 images per test in each category, the accuracy of the algorithm is 99%, respectively the error rate is 1%. If are taken 40 images per category, the accuracy of the algorithm is 99%, respectively the error rate is 1%. If are taken 15 images per category, the accuracy of the algorithm is 94%, respectively the error rate is 6%. If are taken 10 images per category, the accuracy of the algorithm is 91%, respectively the error rate is 9%.

From the results presented, we can see that in the second case, as in the first case, if the number of images per category is greater, the accuracy of the algorithm is greater, respectively the lowest error rate. If the number of images per category is smaller, the accuracy of the algorithm is smaller, respectively the highest error rate. However, if we compare the results obtained in the second case with the results obtained in the first case it will be seen that in the second case the accuracy of the algorithm is much better. In other words, if we have grouped images in only two groups (the second case), the performance of the algorithm has improved considerably.

Also this algorithm will send to border police patrols, image captured by the sensor nodes. Thus, border police patrols will receive the image in real time and will not need any other additional confirmation. This will directly impact on the efficiency of border patrols in preventing the illegal activities along the border.

VI. CONCLUSIONS

To eliminate false alarms from sensor nodes, identification and classification of images captured has a special significance. Therefore in this paper, we proposed a new algorithm which is very efficient in classification and identification of an image from another image. Results obtained through simulations and presented in this paper, illustrated that this algorithm is very suitable to be applied for purposes of eliminating false alarms from sensor nodes. This will directly impact the efficiency of border patrols. In the future, this algorithm remains to be tested in a practical way in the centre of state border monitoring, so that we can see the results of the practical implementation of this algorithm.

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