Mobile multirobot manipulation by image recognition

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Abstract**—** In this paper we considered the problem of mobile multirobot manipulation, with information extracted from a fixed position camera for command inputs that is analyzed by a real time image recognition algorithm. We used 1320 images for training 11 gesture commands, for decision making we used deep learning through a CNN. The proposed method is evaluated using Kappa's agreement analysis, with overall score (*K*), of 0.9708, meaning almost perfect agreement between the prediction of the CNN and the result expected. This approach allows multiple robotic agents to perform collaborative tasks in real time using hand gestures.

Keywords**—**Deep Learning, Image recognition, Manipulation, Multirobots.

I. Introduction

The control for multirobot systems received significant attention, and is concerned about the way of positioning and order of displacement of the agents, as was done in [1]. Multirobot applications can be found across multiple domains. For example, in search and rescue scenarios [2], coverage for surveillance and exploitation [3], objects manipulation [4]. There are applications for air and sea enviroments [5], [6], [7].

The main contribution in this work is the approach of the control of multirobots, through the recognition of predefined images of trajectory and the design of the controller for the distribution and manipulation of coordinates. The images are contained as a standard in a database that describe their interacting behavior with the environment. The hand gestures recognition was implemented using deep learning, Convolutional Neural Network (CNN), which guarantees a robust coverage in image recognition under certain assumptions that will be clarified throughout the text in robotic simulation. The developed structure allows the simulated robot to maintain or change the formation of the specified trajectories and to perform tasks of either individual or collaborative manipulation.

The paper is divided in 5 sections, in which section 2 is characterized by the configuration of the problem, where is discussed and presented solutions already performed. It follows the formulation of the central algorithm applied in section 3, and the statistical method to verify the reliability. Results after the application of the proposal is given in section 4 and the conclusion in section 5.

II. Multirobot control

Several researchers have proposed models for robot control and multirobots. One of known models is proposed by Umari [8], establishing autonomous exploration established by rapidly-exploring randomized trees that direct the robots into uncharted space through the detection of boundaries by processing images to find the edges.

Aguiar [9] conducts research in area of motion control for autonomous robotics vehicles. This paper presents a brief research related to trajectory tracking and the problem of making groups of autonomous robotic vehicles follow the desired geometric paths, maintaining a specific training pattern, cooperative.

In [10] the work focuses mainly on modeling and control improved by computational intelligence, so that it can have flexible robots with a wide range of operation and can get involved with less instructions. In this work, there is a greater concern with sensor technology to reduce uncertainly. The autonomous multiple robotic systems has also been studied for cooperative and competitive work.

In paper of [11] is proposed an approach for hierarchical coalition. The proposed approach is conducted under a hierarchical structure, which is composed of lower-level individual robots and higher-level managers. Different managers can be combined when necessary to meet the resource requirements of some complex tasks.

Liu [12] investigates the consensus of adaptive group of multiple robotics manipulator in the task space under topology of directed acyclic graphs. Two strategies of adaptive control are proposed: one based on the method of linearity of the parameters and another in the neural network method.

In [13] were developed a scenario of cooperative assembly of multiple components in different locations. It consists of two phases, including cooperative capture and transport, respectively.

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The paper of [14] presents the strategy of collaboration of multiple robotic fishes based on the planning of the mission and in the effective area. According to the idea of allocation of tasks based on the area, the fish are divided.

In [15] the coordination control of multiple robotic fishes is developed in highly dynamic aquatic environments, constructing a centralized hybrid system. With the help of the results of the control and bio robotic techniques, a multi-junction robotic fish controlled by radio and its control of locomotion was developed. To enable a closed-loop circuit, a visual subsystem that is responsible for tracking multiple moving objects is constructed and implemented in real-time.

With the advancement of computer vision improvements have occurred in the recognition of human action based on video and the recognition of patterns. In [16] is conducted a review of several advanced techniques based on advanced learning for the recognition of human action and applications such as robotics.

In [17] the online learning of hand gestures in robotic multi-robot systems is approached in an innovative way. It addresses the problem of online learning resources, proposing Convolval Max-Pooling (CMP), a simple two-layered network derived from the hierarchical network Max-Pooling Convalineal Neural (MPCNN). To learn and classify gestures in an online and incremental way.

Based on these multi-robot searches and the innovative approach to performing gesture control, we established the creation of a detailed multi-robot control in section 3.

III. Methodology

In this section the structure of the adopted system will be demonstrated, the hand gestures acquired and stored, the structure of the algorithm, finalizing with the method of classification agreement analysis

A. *Structure of the system*

The structure of the adopted system is shown in Fig. 1

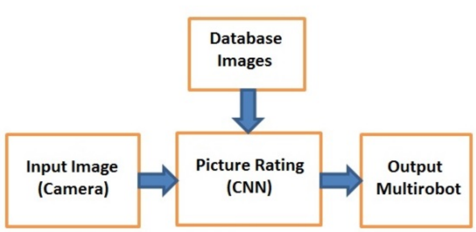

Fig. 1 Schematic of the adopted system.

There is a camera that captures the real-time input signal from the hand gestures, soon after it is interpreted by the CNN algorithm, which compares the input image with the database. After a comparison, a signal is sent to the robots.

B. *Hand gestures*

For this work, 1320 images of hand signals were used for system training and testing, the images were provided by [18], [19], being that for this problem, was pre-processed in order to adapt the images so that they obeyed the criteria of CNN (subsection III.C). The image set is divided into 11 gestures categories, each one with 120 samples. Each category corresponds to a hand gesture, which in turn represents a command sent to the robots, according to Fig. 2.

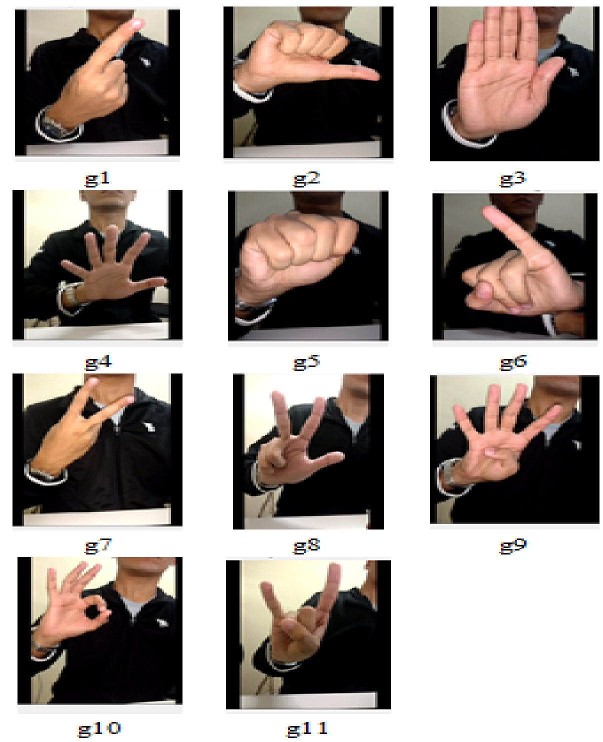

Fig. 2 example of hand gestures used to manipulate the robots.

The interpreted commands are of two types of activity: collective command and the individual ones. To select between collective or individual action the signal "g1" is used for a certain period of time. Holding the gesture in front of the camera for up to three seconds will cause the individual action type to be selected. Holding the gesture for a period of time greater than three seconds will cause all actions passed to the robots to be collective. To start and finish a given function are performed respectively signals "g2" and "g3".

In collective commands the information is sent to all robots and perform the gather and spread functions using the "g5" and "g4" signals, respectively.

To choose the robot individually, it is necessary to make a signal for each of them, "g6", "g7", "g8" and "g9" signals, each of these gestures will cause a robot to be selected for a certain action. There are commands that are common to robots, whether in collective or individual mode: turn right, gesture "g10" up to three seconds, turn left, gesture "g10" for more than three seconds, backwards, gesture "g11" up to three seconds and moves forwards, gesture "g11" for more than three seconds.

Later, these images were used to perform the training in the CNN algorithm.

C. *CNN*

The CNN algorithm has been used with great success in obtaining results in complex problems. The deep learning with neural networks is discussed and diffused nowadays mainly in the area of computer vision.

A convolutional neural network is a variant of perceptron multilayer networks. It is inspired by the biological process of processing visual data and is made up of multiple parts each with different functions. They consist of neurons that have weights and learnable tendencies. Each neuron receives some inputs, executes a dot product, and optionally follows it with a non-linearity. The entire network still expresses a single differentiable punctuation function: from the pixels of the raw image at one end to the punctuation of the class at the other. And they still have a loss function, in this paper we used a CNN as an attribute extractor for another dataset.

The CNN architecture used was AlexNet. Proposed by Krizhevsky [20]. Its architecture is quite similar to that of LeNet-5, but it is deeper, with more convolutional layers, and has many more feature maps, as shown in Fig 3.

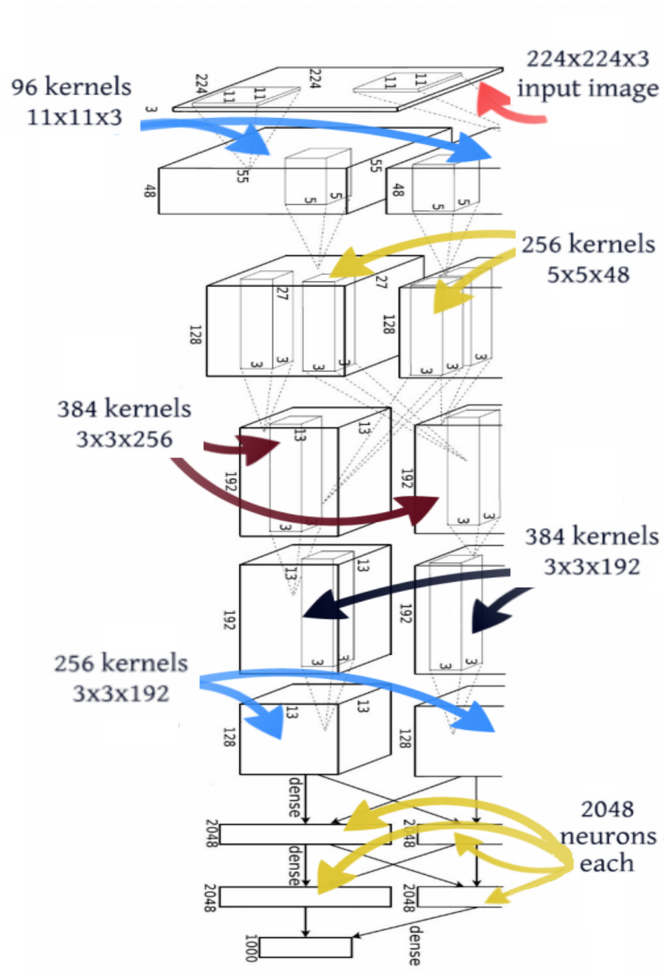

Fig. 3 Architecture of the CNN used in this work. The output layer was altered in order to fit the criteria of this approach.

AlexNet receives as input 224 x 224 pixels per channel. In the first convolution layer it uses a filter 11 x 11 x 3, in the second 5 x 5 x 3 and in the third a 3 x 3 x 3. In addition, the third, fourth and fifth layers are connected without the use of pooling. Finally, the network has two layers fully connected with 2048 neurons each and an output layer with 1000 neurons, the number of classes in the problem. It is worth noting that AlexNet was the first network to use dropout [20] to assist in the training of the fully connected layer.

For this work, the transfer learning technique was adopted to accelerate the training process, using the structure of the AlexNet network, changing the output layer to 11 neurons according to the categories of gestures to be classified, thus not having to train all the weights of the layers of the network, which would be a costly process.

The imageset was divided in 60 percent (792 images) for training the network, and 40 percent (528) for evaluating the network precision.

D. Classification agreement analysis

The proposed method is evaluated through the confusion matrix, a statistical tool that provides the basis to describe the accuracy of the classification and characterize the errors, helping to refine the classification. From a confusion matrix can be derived several measures of accuracy of the classification.

The confusion matrix is formed by an array of squares of numbers arranged in rows and columns expressing the number of sample units of a particular relative category inferred by a decision rule compared to the current category found in the field. Normally below the columns is represented the set of reference data that is compared to the data of the classification product that are represented along the lines. The Table III shows the confusion matrix containing the results of this approach. The elements of the main diagonal, in bold, indicate the level of accuracy, or agreement, and between the two sets of data which is, in this case, one of the criteria for evaluation of efficiency of the proposed method.

The measures derived from the confusion matrix are: total accuracy, individual class accuracy, producer precision, user precision and Kappa index, among others. The total accuracy (*T*) is calculated by dividing the sum of the main diagonal of the error matrix x_{ii}, by the total number of samples collected *n*. According to equation 1.

$$T = \frac{\sum_{i=1}^{a} x_{ii}}{n} \tag{1}$$

The accuracy distribution across individual categories is not shown in the overall precision, however, the accuracy of an individual category is obtained by dividing the total number of samples correctly classified in that category by the total number of samples in that category. In [21] is described the calculations associated with these measures.

In this work, the Kappa measure is used to describe the intensity of the agreement, which is based on the number of concordant responses. Kappa is a measure of inter observer agreement and measures the degree of agreement beyond what would be expected by chance alone. Used on nominal scales, it gives an idea of how far observations depart from those expected, the result of chance, thus indicating how legitimate interpretations are.

It is a discrete multivariate technique used in the evaluation of thematic accuracy and uses all the elements of the confusion matrix in its calculation. The Kappa coefficient (K) is a measure of the actual agreement (indicated by the diagonal elements of the confusion matrix) minus chance agreement (indicated by the total product of the row and column, which does not include unrecognized entries), that is, a measure of how far according to the reference data. The Kappa coefficient can be calculated from equation 2:

This measure of agreement has as maximum value 1, where this value 1 represents the total agreement and the values close to 0 indicate no agreement, or the agreement was exactly generated by chance. An eventual value of Kappa less than zero, negative, suggests that the agreement found was less than expected by chance. It suggests, therefore, disagreement, but its value has no interpretation as an intensity of disagreement.

$$k = \frac{n\sum_{i=1}^{a} x_{ii} - \sum_{i=1}^{a} x_{+i}x_{ii}}{n^2 - \sum_{i=1}^{a} x_{+i}x_{ii}} \tag{2}$$

The interpretation of Kappa values is suggested in [22] according to Table I.

Table I. Values of Kappa interpretation.

Output	Level of agreement
< 0	No agreement
0 – 0.19	Poor agreement
0.20 – 0.39	Fair agreement
0.40 – 0.59	Moderate agreement
0.60 – 0.79	Substantial agreement
0.80 – 1.00	Almost perfect agreement

Around the Kappa value confidence intervals can be calculated using the variance of the sample (*var*) and the fact that the statistical distribution of Kappa is normally asymptotic. [21] suggests means of testing the statistical significance of Kappa for a single confusion matrix, through variance, in order to determine if the correctness level of the classification and the reference data are significantly greater than zero. The statistical test to test the significance of a single confusion matrix is determined by equation 3.

$$Z = \frac{K}{\sqrt{var\,(K)}} \tag{3}$$

Where Z is unified and normally distributed and *var* is the large variance of the Kappa coefficient sample, which can be calculated using the Delta method as follows equation 4.

$$var(k) = \frac{1\theta_1(1-\theta_1)}{n(1-\theta_1)^2} + \frac{2(1-\theta_1)(2\theta_1}{(1-\theta_2)} + \frac{(1-\theta_1)^2\left(\theta_4 - 4{\theta_2}^2\right)}{(1-\theta_2)^4} \tag{4}$$

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where, $\theta_1 = \frac{1}{n}\sum_{i=1}^{c} x_{ii}$, $\theta_2 = \frac{1}{n^2}\sum_{i=1}^{c} x_{i+}x_{+i}$, $\theta_3 = \frac{1}{n^2}\sum_{i=1}^{c} x_{ii}(x_{i+} + x_{+i}) = \frac{1}{n}\sum_{i=1}^{c} x_{ii}$, $\theta_4 = \frac{1}{n^3}\sum_{i=1}^{c}\sum_{j=1}^{c} x_{ij}(x_{j+} + x_{+j})^2$. if $z \geq z_{\frac{\alpha}{2}}$ the classification is significantly better than a random distribution, where $\frac{\alpha}{2}$ the level of confidence on both sides of the test curve Z and the number of degrees of freedom is assumed to be infinite.

IV. RESULTS

In this section, the proposed method is evaluated qualitatively, using the validation techniques proposed in the section *III. D* , where the accuracy of the CNN is measured by means of the discriminant analysis between the input image and the result produced, and also by the Kappa index.

In Table II is displayed two fine tunings used for CNN training. The CNN processing was performed using a GTX 1050ti video card, which has 768 CUDA cores (processors) and a Intel Core i3 processor, with 16 Gigabytes of RAM, although, the most of processing effort is done by video card, since AlexNet was written for running on GPUs, if available.

Table II. Training parameters used in the CNN.

Order	Initial Learn Rate	Mini Batch Size	Max Epochs	Accuracy	Time spent (min)
01	0.01	64	10	0.9016	08
02	0.001	300	20	0.9766	22

The processing time is relatively short if using the standard parameters of the original CNN, according to Table II using parameter #01, an accuracy of 90.16% was obtained, with an average processing time of 08 minutes. With fine tuning #02, by doubling the epoch parameter (the number of times the dataset is parsed in each layer) and by extending the number of observations (Mini Batch Size) to 300, we obtained 97.66% of accuracy, however the training time increased to 22 minutes.

In the Table III it is observed that the accuracy surpasses 90% for each gesture evaluated, being the general accuracy highest than 97%, with the worst case for the gestures "g8" and "g9", with 93.8% each. The classes may have different sum to 100 due to rounding effects.

The Table IV shows the result obtained after the analysis of the confusion matrix using agreement analysis, where the value K is calculated according to the given matrix, being the result of 0.9708, meaning almost perfect agreement (see Table I) between the elements predicted by the algorithm and those already known previously, thus corroborating the analysis of accuracy of the matrix presented in the Table III. It is still displayed the significance test (Z), given the variance of 0.0002 which implicates in a rating significantly better than a random distribution (see equation 3) among other values.

The Fig. 4 depicts the evaluation of the webcam stream, while the robots execute the "g4" command, ordering them to spread in different directions, the algorithm presents a satisfactory response time, being the gesture recognition done in real-time.

Below is the pseudocode that represents the action of the robot in Fig.4. First, the four robots are loaded in a three-dimensional scenario, then a stream of images of the webcam is captured, where each image coming from this stream are evaluated on CNN. If the classified image category matches the command to which the robot waits to perform a task, then this will perform this task until another command is given.

Table III. Confusion matrix of the proposed approach, the number of true positive is expressed in the main diagonal, in bold, being this higher than 97%, the classes evaluated corresponds to gestures in Fig.2.

	Predicted %										
Known	**g1**	**g2**	**g3**	**g4**	**g5**	**g6**	**g7**	**g8**	**g9**	**g10**	**g11**
g1	**97.9**	-	-	-	-	2.1	-	-	-	-	-
g2		**100**	-	-	-	-	-	-	-	-	-
g3	-	-	**97.9**	2.1	-	-	-	-	-	-	-
g4	2.1	-	-	**95.8**	-	2.1	-	-	-	-	-
g5	-	-	-	2.1	**97.9**	-	-	-	-	-	-
g6	-	-	-	-	2.1	**97.9**	-	-	-	-	-
g7	-	-	-	-	-	-	**100**	-	-	-	-
g8	-	-	-	4.1	-	2.1	-	**93.8**	-	-	-
g9	-	2.1	-	-	-	-	-	-	**93.8**	-	4.1
g10	-	-	-	-	-	-	-	-	-	**100**	-
g11	-	-	-	-	-	-	-	-	4.2	-	**95.8**

```
begin
load robot1, robot2, robot3, robot4
load myCNN
webcam = WebCam()
loop
    myImage = webcam.snapShot()
    myPrediction = predict(myImage,myCNN)
    if myPrediction equal "g4" then
        spreadRobots()
    else
        if myPrediction not equal "g4" then
            doOtherStuff()
end
```

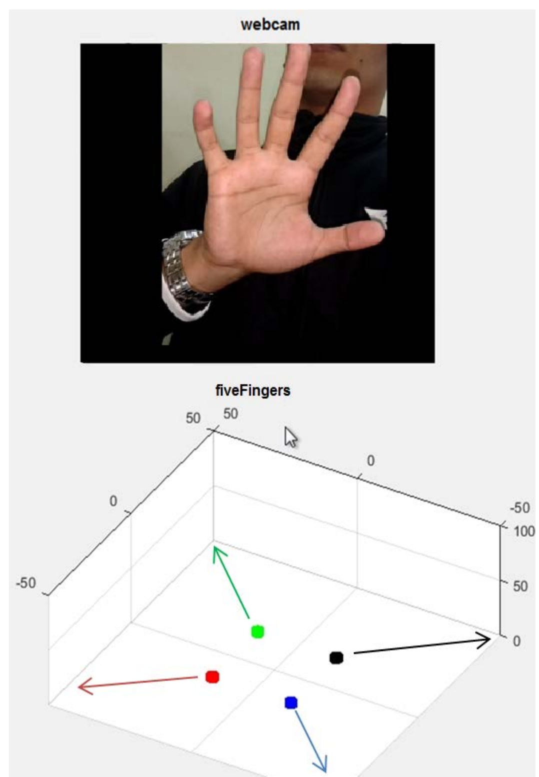

Fig. 4 Spread command (g4) manipulating four robots using gesture.

Table IV. Kappa agreement analysis

Observed agreement (po)	0.9735
Random agreement (pe)	0.0909
Agreement due to concordance (po-pe)	0.8826
Residual not random agreement (1-pe)	0.9091
K	0.9708
Kappa error	0.0077
Alpha	0.0500
Maximum possible Kappa	0.9896
Variance	0.0002
Z	70.5368

V. CONCLUSION

This paper presents the control of multi-robots from hand gestures, which can be a robust alternative of command. In addition, a good accuracy of the chosen algorithm of 97.66% and a Kappa index of 0.9708 is observed. The experimental results demonstrate the feasibility of the proposed approach.

Compared with the method proposed by [19] which for evaluation of the same image set, obtains results close to 90% in the best case, being some categories classified with 80% accuracy, this work presents very competitive results, with accuracy of 93,8% in worst case, and overall accuracy of 97.66%. This being so, the use with multi-robots propitious due to its high rate of correctness.

The algorithm also presents a satisfactory response when processing real-time video and evaluating and translating the operator's actions into actions for the robots so that they perform tasks immediately [23].

Future work is intended to increase the number of gestures and images. It is also intended to test the system with Microsoft Kinect device and compare this method with other decision algorithms.

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