Invariant moment and learning vector quantization (LVQ NN) for images classification

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Abstract. Image classification need two main components, i.e., features and classifier. The feature commonly used for classification of images with different scale is invariant moment; its value is invariant against the spatial transformation dealing with translation, scale and rotation. The classifier that is widely used for classification is LVQ NN. It is shallow network containing only two layers, the initial value of its weight is more fixed so that its output is more stable and its algorithm is relatively simple thus both training and testing process are run fast. Based on these facts, therefore, this research proposed a combination method of invariant moment and LVQ NN (IM-LVQ). The ability of the proposed method would be compared with two other methods. Firstly, the combination method of invariant moment and Euclidean distance (IM-ED). Secondly, the combination of invariant moment and principal component analysis (IM-PCA). The performance of the three methods was evaluated quantitatively with several metrics, viz.: Confusion Matrix, Accuracy, Precision, True Positive Rate, False Positive Rate, ROC graph and training time. The evaluation of the metrics was based upon the changing (reduction) of the scale/size of training image. The results showed that IM-LVQ method outperformed the other two methods in aforementioned metrics.

1. Introduction
In the field of image processing, features commonly used for image classification are: shape, color and texture. Shape features are related to semantic meaning and are considered as features of a higher level than that of color and texture ones. The shape feature commonly used is Hu's invariant moment. This is based on the fact that the Hu's invariant moment represents global features and its value is invariant (unchanging) that is not influenced by the spatial transformation associated with translation, scale and rotation [1, 2]. The invariant nature of the scale of the moment allows the scale or size of the sample images to have different sizes or scale. Reducing the scale of the image means that it can speed up computing time. This is the advantage of the Hu’s invariant moment features compared with other features. Invariant moments have been used in several studies as features for the process of identifying or classifying objects [1, 3-5]. The value of invariant moment will be used as input for classifiers in the classification process.

A number of classifiers commonly used i.e.: neural network-based classifiers (e.g.: Learning Vector Quantization Neural Network (LVQ NN), Multi-Layer Perceptron Neural Network (MLP NN), Convolutional Neural Network (CNN)), distance-based ones (e.g.: Euclidean, Manhattan, Mahalanobis), Principal Component Analysis (PCA), K-Nearest Neighbor (KNN), Support Vector Machine (SVM) and so on. In this study, the LVQ NN classifier is proposed based on several considerations as described below.
LVQ NN is a shallow neural network consisting only two layers, namely: input and output. LVQ NN is stable, i.e., it returns the stable output affected by the initial value of weights is more fixed. The training and testing process both are run rapidly caused by its algorithm is relatively simple and requires a small number of parameters that need to be set. The testing process for the classification of new samples can be done easily by calculating the Euclidean distance from the new sample feature with the sample feature in the database. This network is able to classify patterns with different number of classes. Some studies show the advantages of LVQ NN compared to other methods [6-8].

Based on aforementioned facts related to the Invariant Moment and LVQ NN methods, therefore, this study proposes a combination of the two methods (IM-LVQ). The IM-LVQ method consists of two stages: training and testing. The training stage aims to train the LVQ NN by using features related to Hu’s seven invariant moments. The results of the training are the weight features which are subsequently stored in the feature database. The testing stage is the process of evaluating the ability of LVQ NN to classify new samples by using the weight features stored in the database.

The ability of the IM-LVQ method will be compared with two other methods, namely, firstly a combination of invariant moment and Euclidean distances (IM-ED) and secondly, a combination of invariant moment and principal component analysis (IM-PCA). The performance of All three methods will be evaluated quantitatively with some metrics, i.e., Confusion Matrix, Accuracy, Precision, True Positive Rate (TP Rate), False Positive Rate (FP Rate), Receiver Operating Characteristics Graph (ROC Graph) and training time [9]. The metrics evaluation is based upon the changing that related to the gradual reduction of scale or size of training images.

2. Experimental Method

2.1. Data for Training and Test

Data or samples used in this study are silhouette images of ship and aircraft. The number of samples used are 120. The number of training and test samples are 20 and 100, respectively. The training and test samples can be seen in Table 1 and Table 2, respectively. By Table 1, training samples are original samples that have not been imposed translation, scale and rotation. Training samples are separated into

| Class | Samples |
|-------|---------|
| Class 1 | ![Image](image1) |
| Class 2 | ![Image](image2) |

| Class | Samples |
|-------|---------|
| Class 1 | ![Image](image3) |
| Class 2 | ![Image](image4) |

Table 1 Training samples

Table 2 Test Samples
2 classes, namely, class 1 (airplane) and class 2 (ship). The testing samples displayed on Table 2 are training ones that have undergone either a process of translation, rotation or scale. Some samples are shown incomplete (e.g., class 1 (row 1, column 2) and class 2 (row 2, column 2)). There are, even, some samples that are slightly changed (e.g., class 1 (row 1, column 4)). In Table 2 only 40 out of 100 test samples are displayed.

2.2. Block Diagram of IM-LVQ
Block diagram of IM-LVQ is divided into two parts, namely, training and testing ones. The block diagram for the training and testing process, respectively, can be seen in Figure 1 (a) and (b).

![Block diagrams for training (a) and testing (b) of IM-LVQ](image)

The training process (Figure 1 (a)) is carried out recurrently 10 times for image scales ranging from 100% down to 10%. The interval of image scale reduction is 10%. Therefore, we will obtain 10 datasets of weight (w) feature as a representation of each scale of training images. Similarly, the testing process (Figure 1 (b)) is also performed repeatedly 10 times on 10 feature datasets representing of each scale. The algorithm of the IM-LVQ refers to the literature [10, 11]. Meanwhile, the IM-ED and IM-PCA methods are implemented based on references [11, 12]. The all of three methods are implemented into source codes by using MATLAB 2017a and a computer with a processor core i3-2.4 GHz, 4 GB of RAM.

3. Result and Discussion

3.1. Training Result Data Related to Image Scale and Training Time
The results of the IM-LVQ, IM-ED and IM-PCA methods, which are associated with image scale and training time are demonstrated in Table 3. The regression results between the image scale and the training time of the three methods are shown in Figure 2.

### Table 3 Data of image scale and training time

| Training Image Scale (x100%) | Training Time (second) | Training Image Scale (x100%) | Training Time (second) |
|-----------------------------|------------------------|-----------------------------|------------------------|
|                             | IM-LVQ | IM-ED | IM-PCA | IM-LVQ | IM-ED | IM-PCA |
| 1.0                         | 17.26  | 16.86 | 15.38  | 0.5    | 6.34  | 5.20   | 4.11   |
| 0.9                         | 14.53  | 14.25 | 12.54  | 0.4    | 3.58  | 3.84   | 2.75   |
| 0.8                         | 11.94  | 11.44 | 9.99   | 0.3    | 2.88  | 2.18   | 1.59   |
| 0.7                         | 9.85   | 9.45  | 7.76   | 0.2    | 1.37  | 1.09   | 0.79   |
| 0.6                         | 7.34   | 7.08  | 5.79   | 0.1    | 1.06  | 0.47   | 0.34   |

The regression of the three methods are associated with 2nd-order polynomial equation. The coefficient of determination ($R^2$) is close to or equal to 1, it means that the independent variable (image scale) hardly
affects the dependent variable (training time). The reduction of image scale will affect training time that is also reduced quadratically corresponding to 2nd-order polynomial equation. On the other hand, the reduction in image scale does not affect the value of testing accuracy for the IM-LVQ method (stable 100%), but for IM-ED and IM-PCA methods in which it is reduced to the lowermost value of 99% and 88%, consecutively, as can be seen by Table 4.

3.2. Data of Testing Result Related to Image Scale, Class and Testing Accuracy

Data of testing result from the IM-LVQ, IM-ED and IM-PCA methods associated with image size, class (1 or 2) and testing accuracy can be seen by Table 4. Class 1 and class 2, respectively, represent aircraft and ship.

**Table 4** Data of testing accuracy for IM-LVQ, IM-ED and IM-PCA methods

| Training Image Scale (100%) | IM-LVQ |             | IM-ED |             | IM-PCA |          |
|-----------------------------|--------|-------------|-------|-------------|--------|-----------|
|                             | Class 1 | Class 2     | Testing accuracy (%) | Class 1 | Class 2 | Testing accuracy (%) | Class 1 | Class 2 | Testing accuracy (%) |
| 1.0                         | 50      | 50          | 100   | 50          | 100    | 50         | 100     |          |
| 0.9                         | 50      | 50          | 100   | 50          | 100    | 50         | 100     |          |
| 0.8                         | 50      | 50          | 100   | 50          | 100    | 50         | 100     |          |
| 0.7                         | 50      | 50          | 100   | 50          | 100    | 50         | 100     |          |
| 0.6                         | 50      | 50          | 100   | 49          | 99     | 50         | 100     |          |
| 0.5                         | 50      | 50          | 100   | 49          | 99     | 50         | 100     |          |
| 0.4                         | 50      | 50          | 100   | 49          | 99     | 49         | 99      |          |
| 0.3                         | 50      | 50          | 100   | 50          | 100    | 47         | 49      | 96       |
| 0.2                         | 50      | 50          | 100   | 51          | 99     | 50         | 39      | 89       |
| 0.1                         | 50      | 50          | 100   | 51          | 99     | 50         | 38      | 88       |

Based on Table 4, 30 confusion matrices can be made from the three methods. Tables 5 and 6, respectively, are the confusion matrix of the IM-LVQ and IM-ED methods for image scales of 100%. In the tables, class 1 (aircraft) is considered as positive class (+) while class 2 (ship) is regarded as negative class (-).

**Table 5** Confusion matrix of IM-LVQ for image scale of 100%

| Actual Class | Predictive class |          |
|--------------|------------------|----------|
|              | Positive (+)     | Negative (-) |
| Positive (+) | 50               | 0        |
| Negative (-) | 0                | 50       |

**Table 6** Confusion matrix of IM-ED for image scale of 100%

| Actual Class | Predictive class |          |
|--------------|------------------|----------|
|              | Positive (+)     | Negative (-) |
| Positive (+) | 50               | 0        |
| Negative (-) | 0                | 50       |
After determination of the confusion matrix, we can determine the metrics, i.e., accuracy, precision, TP rate and FP rate. The performance metrics of the IM-LVQ, IM-ED and IM-PCA methods are presented in Tables 7, 8 and 9, consecutively.

**Table 7** The performance metrics of IM-LVQ

| Scale (100%) | Accuracy | Precision | FP Rate | TP Rate |
|--------------|----------|-----------|---------|---------|
| 1.0          | 1        | 1         | 0.00    | 1       |
| 0.9          | 1        | 1         | 0.00    | 1       |
| 0.8          | 1        | 1         | 0.00    | 1       |
| 0.7          | 1        | 1         | 0.00    | 1       |
| 0.6          | 1        | 1         | 0.00    | 1       |
| 0.5          | 1        | 1         | 0.00    | 1       |
| 0.4          | 1        | 1         | 0.00    | 1       |
| 0.3          | 1        | 1         | 0.00    | 1       |
| 0.2          | 1        | 1         | 0.00    | 1       |
| 0.1          | 1        | 1         | 0.00    | 1       |
| **Average**  | 1        | 1         | 0.00    | 1       |

**Table 8** The performance metrics of IM-ED

| Scale (100%) | Accuracy | Precision | FP Rate | TP Rate |
|--------------|----------|-----------|---------|---------|
| 1.0          | 1        | 1         | 0.00    | 1       |
| 0.9          | 1        | 1         | 0.00    | 1       |
| 0.8          | 1        | 1         | 0.00    | 1       |
| 0.7          | 1        | 1         | 0.00    | 1       |
| 0.6          | 1        | 1         | 0.00    | 1       |
| 0.5          | 0.99     | 1         | 0.00    | 0.98    |
| 0.4          | 0.99     | 1         | 0.00    | 0.98    |
| 0.3          | 0.99     | 0.98      | 0.02    | 1       |
| 0.2          | 0.99     | 0.98      | 0.02    | 1       |
| 0.1          | 0.99     | 0.98      | 0.02    | 1       |
| **Average**  | 0.996    | 0.996     | 0.004   | 0.996   |

**Table 9** The performance metrics of IM-PCA

| Scale (100%) | Accuracy | Precision | FP Rate | TP Rate |
|--------------|----------|-----------|---------|---------|
| 1.0          | 1        | 1         | 0.00    | 1       |
| 0.9          | 1        | 1         | 0.00    | 1       |
| 0.8          | 1        | 1         | 0.00    | 1       |
| 0.7          | 1        | 1         | 0.00    | 1       |
| 0.6          | 0.96     | 1         | 0.00    | 0.92    |
| 0.5          | 0.99     | 1         | 0.00    | 0.98    |
| 0.4          | 0.96     | 0.98      | 0.02    | 0.94    |
| 0.3          | 0.89     | 0.82      | 0.22    | 1       |
| 0.2          | 0.88     | 0.81      | 0.24    | 1       |
| 0.1          | 0.88     | 0.81      | 0.24    | 1       |
| **Average**  | 0.968    | 0.961     | 0.048   | 0.984   |

Tables 7, 8 and 9 show average values of the accuracy, precision and TP Rate for the IM-LVQ method are closer to or equal to 1 and the FP rate value is closer to or equal to 0 than the IM-ED and IM-PCA methods. Hence, it can be stated that the IM-LVQ method is better than the other ones. The average values of FP rate and TP rate can be used to determine the coordinate points on the ROC Graph of the three methods as presented in Figure 3. The coordinates (FP Rate, TP Rate) of the IM-LVQ method are located at coordinates (0, 1) represented by yellow point. The IM-ED method is located at coordinates (0.004, 0.996) denoted by red point. Whereas the IM-PCA method is located at coordinates (0.048, 0.984) and it is expressed using green point.

![Figure 3 ROC graph of the three methods](image-url)
In order to determine the best method of the three methods, then Euclidean distance is calculated from the three points (yellow, red, green) to the point with coordinates (0,1) (perfect classifier) [9]. The closer the Euclidean distance then the better the method is. The Euclidean distance for the IM-LVQ, IM-ED and IM-PCA methods, respectively, are 0, 0.006 and 0.051. It can be seen that Euclidean distance of IM-LVQ method is the closest one. Thus, among the three methods could be decided that IM-LVQ is the best one.

4. Conclusion
The performance of the IM-LVQ method outperformed the IM-ED and IM-PCA ones in classifying patterns. This can be seen both from its most optimal value of accuracy, precision, FP Rate, TP Rate and the closest Euclidean distances on ROC Graph. The reduction in training image scale reducing training time in all three methods but the IM-LVQ method returns the most stable value of testing accuracy compared to the other two methods.

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