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K. Ashok Kumar

Dept of ECE, V.R.S & Y.R.N college of Engg & Tech., Chirala, Andhra Pradesh, ashok.kavuru@gmail.com

Y.V. Bhaskar Reddy

Dept of ECE, Q.I.S college of Engg & Tech., Ongole, Andhra Pradesh, yvbreddy06@yahoo.com

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Content Based Image Retrieval Using SVM Algorithm

K. Ashok Kumar & Y.V.Bhaskar Reddy

Dept of ECE, V.R.S & Y.R.N college of Engg & Tech., Chirala, Andhra Pradesh
Dept of ECE, Q.I.S college of Engg & Tech., Ongole, Andhra Pradesh
E-mail : ashok.kavuru@gmail.com, yvbreddy06@yahoo.com

Abstract - Conventional content-based image retrieval (CBIR) schemes employing relevance feedback may suffer from some problems in the practical applications. First, most ordinary users would like to complete their search in a single interaction especially on the web. Second, it is time consuming and difficult to label a lot of negative examples with sufficient variety. Third, ordinary users may introduce some noisy examples into the query. This correspondence explores solutions to a new issue that image retrieval using unclean positive examples. In the proposed scheme, multiple feature distances are combined to obtain image similarity using classification technology. To handle the noisy positive examples, a new two step strategy is proposed by incorporating the methods of data cleaning and noise tolerant classifier. The extensive experiments carried out on two different real image collections validate the effectiveness of the proposed scheme.

Index Terms—Classifier combination, content-based image retrieval (CBIR), feature aggregation, noise tolerant, support vector machine(SVM).

I. CLASSIFICATION USING UNCLEAN TRAINING EXAMPLES

1. Shape
2. Texture
3. Color

Quadratic Distance Metric Learning algorithm We used Global colour histograms in extracting the colour features of images. In analyzing the histograms there were a few issues that had to be dealt with. First there was the issue of how much we would quantize the number of bins in a histogram. By default the number of bins represented in an image's colour histogram using the `imhist()` function in MatLab is 256. Meaning that in our calculations of similarity matrix and histogram difference, the processing would be computationally expensive.

Initially we decided to quantize the number of bins to 20. This means that colours that are distinct yet similar are assigned to the same bin reducing the number of bins from 256 to 20. This obviously decreases the information content of images, but decreases the time in calculating the colour distance between two histograms. On the other hand keeping the number of bins at 256 gives a more accurate result in terms of colour distance. Later on we went back to 256 bins due to some inconsistencies obtained in the colour distances between images. This had nothing to do with quantizing the image but rather with the types of images

we were using which will be further elaborated later on in the Results section.

II. SIMILARITY MATRIX

As can be seen from the colour histograms of two images **Q** and **I** in the figure below, the colour patterns observed in the colour bar are totally different. This is further confirmed when one sees the respective colour maps in the following table...

This is the main reason for using the quadratic distance metric. More precisely it is the middle term of the equation or similarity matrix **A** that helps us overcome the problem of different colour maps. The similarity matrix is obtained through a complex algorithm:

$$a_{q_i} = 1 - \frac{\left[\left(v_q - v_i \right)^2 + \left(s_q \cos(h_q) - s_i \cos(h_i) \right)^2 + \left(s_q \sin(h_q) - s_i \sin(h_i) \right)^2 \right]^{\frac{1}{2}}}{\sqrt{5}}$$

The application performs a simple colour-based search in an image database for an input query image, using colour histograms. It then compares the colour histograms of different images using the Quadratic Distance Equation. Further enhancing the search, the application performs a texture-based search in the colour results, using wavelet decomposition and energy level calculation. It then compares the texture features obtained using the Euclidean Distance Equation. A more

detailed step would further enhance these texture results, using a shape-based search.

CBIR is still a developing science. As image compression, digital image processing, and image feature extraction techniques become more developed, CBIR maintains a steady pace of development in the research field. Furthermore, the development of powerful processing power, and faster and cheaper memories contribute heavily to CBIR development. This development promises an immense range of future applications using CBIR.

III. SVM BASED FEATURE EXTRACTION

Firstly working with neural networks for supervised and unsupervised learning showed good results while used for such learning applications. MLP's uses feed forward and recurrent networks. Multilayer perception (MLP) properties include universal approximation of continuous nonlinear functions and include learning with input-output patterns and also involve advanced network architectures with multiple inputs and outputs.

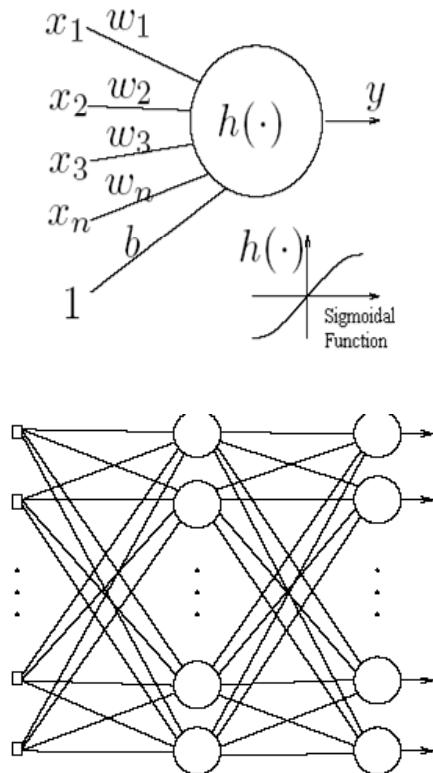


Figure 2: a] Simple Neural Network b]Multilayer Perceptron. These are simple visualizations just to have an overview as how neural network looks like.

There can be some issues noticed. Some of them are having many local minima and also finding how many neurons might be needed for a task is another issue which determines whether optimality of that NN is reached. Another thing to note is that even if the neural network solutions used tends to converge, this may not result in a unique solution. Now let us look at another example where we plot the data and try to classify it and we see that there are many hyper planes which can classify it.

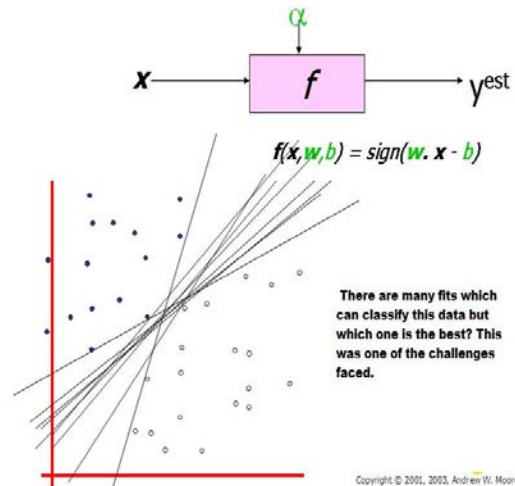


Figure 3: Here we see that there are many hyper planes which can be fit in to classify the data but which one is the best is the right or correct solution. The need for SVM arises. Note the legend is not described as they are sample plotting to make understand the concepts involved.

From above illustration, there are many linear classifiers (hyper planes) that separate the data. However only one of these achieves maximum separation. The reason we need it is because if we use a hyper plane to classify, it might end up closer to one set of datasets compared to others and we do not want this to happen and thus we see that the concept of maximum margin classifier or hyper plane as an apparent solution. The next illustration gives the maximum margin classifier example which provides a solution to the above mentioned problem

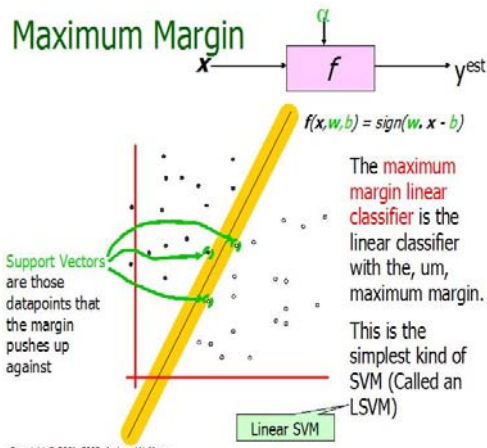


Figure 4: Illustration of Linear SVM. Note the legend is not described as they are sample plotting to make understand the concepts involved.

Expression for Maximum margin is given as (for more information visit

The above illustration is the maximum linear classifier with the maximum range. In this context it is an example of a simple linear SVM classifier. Another interesting question is why maximum margin? There are some good explanations which include better empirical performance. Another reason is that even if we've made a small error in the location of the boundary this gives us least chance of causing a misclassification. The other advantage would be avoiding local minima and better classification. Now we try to express the SVM mathematically and for this tutorial we try to present linear SVM. The goals of SVM are separating the data with hyper plane and extend this to non-linear boundaries using kernel trick. For calculating the SVM we see that the goal is to correctly classify all the data. For mathematical calculations we have,

- [a] If $Y_i = +1$;
- [b] If $Y_i = -1$; $w \cdot x_i + b \leq -1$
- [c] For all i ; $y_i (w \cdot x_i + b) \geq 1$

In this equation x is a vector point and w is weight and is also a vector. So to separate the data [a] should always be greater than zero. Among all possible hyper planes, SVM selects the one where the distance of hyper plane is as large as possible. If the training data is good and every test vector is located in radius r from training vector. Now if the chosen hyper plane is located at the farthest possible from the data. This desired hyper plane

which maximizes the margin also bisects the lines between closest points on convex hull of the two datasets. Thus we have [a], [b] & [c].

Distance of closest point on hyperplane to origin can be found by maximizing the x as x is on the hyper plane. Similarly for the other side points we have a similar scenario. Thus solving and subtracting the two distances we get the summed distance from the separating hyperplane to nearest points.

$$\text{Maximum Margin} = M = 2 / \|w\|$$

Now maximizing the margin is same as minimum. Now we have a quadratic optimization problem and we need to solve for w and b . To solve this we need to optimize the quadratic function with linear constraints. The solution involves constructing a dual problem and where a Lagrange's multiplier α_i is associated. We need to find w and b such that $\Phi(w) = \frac{1}{2} \|w'\|^2$ is minimized;

$$\text{And for all } \{(x_i, y_i)\}: y_i (w \cdot x_i + b) \geq 1.$$

Now solving: we get that $w = \sum \alpha_i \cdot x_i$, $b = y_k - w \cdot x_k$ for any x_k such that $\alpha_k \neq 0$

Now the classifying function will have the following form: $f(x) = \sum \alpha_i y_i x_i \cdot x + b$

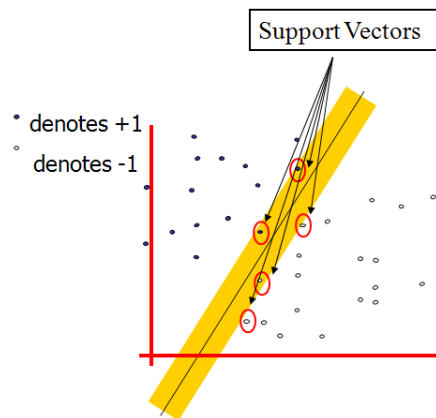


Figure 6: Representation of Support Vectors

IV. SVM REPRESENTATION

In this we present the QP formulation for SVM classification. This is a simple representation only.

SV classification:

$$\min_{f, \xi_i} \|f\|_k^2 + C \sum_{i=1}^l \xi_i \quad y_i f(x_i) \geq 1 - \xi_i, \text{ for all } i \quad \xi_i \geq 0$$

SVM classification, Dual formulation:

$$\min_{\alpha_i} \sum_{i=1}^l \alpha_i - \frac{1}{2} \sum_{i=1}^l \sum_{j=1}^l \alpha_i \alpha_j y_i y_j K(\mathbf{x}_i, \mathbf{x}_j) \quad 0 \leq \alpha_i \leq C, \text{ for all } i$$

Variables ξ_i are called slack variables and they measure the error made at point (\mathbf{x}_i, y_i) . Training SVM becomes quite challenging when the number of training points is large. A number of methods for fast SVM training have been proposed.

V. SOFT MARGIN CLASSIFIER

In real world problem it is not likely to get an exactly separate line dividing the data within the space. And we might have a curved decision boundary. We might have a hyper-plane which might exactly separate the data but this may not be desirable if the data has noise in it. It is better for the smooth boundary to ignore few data points than be curved or go in loops, around the outliers. This is handled in a different way; here we hear the term slack variables being introduced. Now we have, $y_i(w \cdot x + b) \geq 1 - S_k$. This allows a point to be a small distance S_k on the wrong side of the hyper plane without violating the constraint. Now we might end up having huge slack variables which allow any line to separate the data, thus in such scenarios we have the Lagrangian variable introduced which penalizes the large slacks.

$$\min L = \frac{1}{2} w'w - \sum \lambda_k (y_k (w \cdot x_k + b) + s_k - 1) + \alpha \sum s_k$$

Where reducing α allows more data to lie on the wrong side of hyper plane and would be treated as outliers which give smoother decision boundary.

Feature Space: Transforming the data into feature space makes it possible to define a similarity measure on the basis of the dot product. If the feature space is chosen suitably, pattern recognition can be easy.

$$\langle x_1 \cdot x_2 \rangle \leftarrow K(x_1, x_2) = \langle \Phi(x_1) \cdot \Phi(x_2) \rangle$$

Note the legend is not described as they are sample plotting to make understand the concepts involved.

Now getting back to the kernel trick, we see that when w, b is obtained the problem is solved for a simple linear scenario in which data is separated by a hyper plane. The Kernel trick allows SVM's to form nonlinear boundaries. Steps involved in kernel trick are given below.

VI. CONCLUSIONS

We addressed a new issue that image retrieval using unclean positive examples. In the proposed scheme, feature aggregation was formulated as a binary classification problem and solved by support vector machine(SVM) in a feature dissimilarity space.

Incorporating the methods of data cleaning and noise tolerant classifier, a new two-step strategy was proposed to handle the noisy positive examples. In step 1, an ensemble of SVMs trained in a feature dissimilarity space is used as consensus filters to identify and eliminate the noisy positive examples. In step 2, the noise tolerant relevance calculation was performed, which associated each retained positive example with a relevance probability to further alleviate the noise influence. A large number of experiments were carried out on a sub-set of Corel image collection and the IAPR TC-12 benchmark image collection. The experimental results show that the proposed scheme outperforms the competing feature aggregation based image retrieval schemes when noisy positive examples present in the query.

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