A Recursive Approach For Multiclass Support Vector Machine
Application to Automatic Classification of Endomicroscopic Videos

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Abstract: The two classical steps of image or video classification are: image signature extraction and assignment of a class based on this image signature. The class assignment rule can be learned from a training set composed of sample images manually classified by experts. This is known as supervised statistical learning. The well-known Support Vector Machine (SVM) learning method was designed for two classes. Among the proposed extensions to multiclass (three classes or more), the one-versus-one and one-versus-all approaches are the most popular ones. This work presents an alternative approach to extending the original SVM method to multiclass. A tree of SVMs is built using a recursive learning strategy, achieving a linear worst-case complexity in terms of number of classes for classification. During learning, at each node of the tree, a bi-partition of the current set of classes is determined to optimally separate the current classification problem into two sub-problems. Rather than relying on an exhaustive search among all possible subsets of classes, the partition is obtained by building a graph representing the current problem and looking for a minimum cut of it. The proposed method is applied to classification of endomicroscopic videos and compared to classical multiclass approaches.

1 INTRODUCTION

The problem of automatic image (or video, or object) classification is to find a function that maps an image to a class or category among a number of predefined classes. An image can be viewed as a vector of high-dimension. In practice, it is preferable to deal with a synthetic signature of lower dimension. Therefore, the two classical steps of image classification are: image signature extraction (Oliva and Torralba, 2001) and signature-based image classification (Cortes and Vapnik, 1995). (Note that the signature extraction step can itself be the result of a learning process (Sivic and Zisserman, 2003).) The classification rule can be learned from a set of training sample images manually classified by experts. This is known as supervised statistical learning where *statistical* refers to the use of samples and *supervised* refers to the sample classes being provided. In this paper, we are interested in the learning aspect of the multiclass[1] problem when using a binary classification approach as a building block. The Support Vector Machine (SVM) (Cortes and Vapnik, 1995) is a well-known binary classifier that will be used in the following. In its original, linear version, it makes it possible to separate two sets of d-dimensional samples (the training sample signatures for two classes) by finding a particular hyperplane, *i.e.*, by determining its two parameters $b \in \mathbb{R}$ and $w \in \mathbb{R}^d$. It does so by maximizing the half-margin $1/\|w\|$ which represents the distance to the nearest training sample of any class. Whenever the two classes are not linearly separable, the soft margin strategy can be used to account for misclassifications and the kernel trick can be applied to extend the SVM method to nonlinear separation (Scholkopf and Smola, 2001). The parameter tuning the soft margin tolerance is usually denoted by C (see Fig. 3).

Among the proposed extensions of binary classification methods (such as the SVM) to multiclass (three classes or more), the one-versus-one and one-versus-all approaches are the most popular ones. Let us suppose that there are $p \geq 3$ classes. The idea of the one-versus-all strategy is to oppose to any of the classes the union of the remaining $p-1$ classes. Then, p SVM classifiers are determined, each one

[1]Traditionally in classification, *multiclass* means "three classes or more" while the two-class case is referred to as binary classification.

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scoring, say, positively for one of the classes. To classify a new image, its signature is tested against all the SVMs and it is assigned to the class with the highest score (largest distance to the SVM hyperplane). The one-versus-one strategy opposes the classes by pair for all possible pairs. Therefore, $\frac{p(p-1)}{2}$ SVMs are determined. For classification, a new image signature is tested against all the SVMs, each SVM votes in favor of one of the two classes it corresponds to, and the image is assigned to the highest voted class. Other methods also learn all the pairwise SVMs (as for one-versus-one) but use a different scheme to predict the class during the classification step. It is the case for the Decision Directed Acyclic Graph (DDAG (Platt et al., 2000)) and the Adaptive Directed Acyclic Graph (ADAG (Kijsirikul et al., 2002)) methods.

As an alternative to these aforementioned strategies, hierarchical methods can be designed. For example, the work done in (Tibshirani and Hastie, 2006) applies clustering techniques to the different classes and considers the widths of the one-versus-one SVM margins to define linkage criteria. This paper presents a recursive learning strategy to extend a binary classification method to multiclass. A tree of SVMs is built using a recursive learning strategy in such a way that a linear worst-case complexity is achieved for classification. During learning, at each node of the tree, a bi-partition of the set of classes is found to determine an optimal separation of the current classification problem into two sub-problems. This decision relies on building a graph representing the current problem and looking for a minimum cut of it. The proposed method is applied to classification of endomicroscopic videos and compared to classical multiclass approaches.

2 WHY A RECURSIVE STRATEGY?

2.1 Motivations

When learning is performed offline (as described in the present context), it is interesting to design a method with a low classification complexity, even if we have to pay the price of a high learning complexity for it. The classification complexities (in terms of number of classes) of the one-versus-one and the one-versus-all strategies are quadratic and linear, respectively. When thinking about a complexity lower than linear, the logarithmic one comes to mind. Recursive (or, equivalently, hierarchical) approaches naturally lead to such performances. Hence, we propose to decompose the original multiclass problem with p classes into two sub-problems (of "similar size", ideally), *i.e.*, involving q_1 and q_2 classes, respectively, with $q_1 + q_2 = p$. Let us denote by *virtual class* the union of classes involved in a sub-problem. Deciding which virtual class a given signature belongs to is a classical binary classification. Then, as long as the sub-problems involve three classes or more, they can be further decomposed into smaller sub-problems. The question is thus to optimally decompose a given p-class problem, $p \geq 3$, into two sub-problems (see Section 3.1).

Another motivation for such a recursive approach is the fair balance between the sub-problems. Indeed, as already mentioned, the two virtual classes resulting from the decomposition of a p-class problem should each gather the same (or almost the same) number of classes, ideally. If all the classes have roughly the same number of training signatures, so will have the virtual classes. It is certainly desirable for the determination of a reliable binary classification rule, as opposed to the case where one virtual class contains much less samples than the other one. This fair balance property also holds for the one-versus-one strategy (unfortunately, as already mentioned, it has a quadratic classification complexity). However, it does not for the one-versus-all strategy which relies on virtual classes gathering either one class or $p-1$ classes.

Finally, with the proposed recursive approach, the successive binary classifications into virtual classes progressively narrow the classification decision down to the assignment of a unique label among the predefined classes. The one-versus-one and one-versus-all approaches do not exhibit such a coherence since several predefined classes can receive votes when testing a signature against the different SVMs. The final classification decision must deal with competing partial decisions. Although the practical solutions[2] make sense, the principle is not fully satisfying. With the one-versus-one strategy, for a signature belonging to, say, class i, it can be further noted that all the SMVs learned to distinguish between class j and class k, $j \neq i$ and $k \neq i$, will be used to decide whether the signature belongs to class j or class k, and these uninformative partial decisions will be accounted for in the final decision. This is know as the *non-competence* problem.

[2]Maximum number of votes for one-versus-one or maximum positive score for one-versus-all.

2.2 Optimizing the Classification Complexity Alone

Let us suppose that there are $p \geq 3$ predefined classes. Let us recall that a q-subset is a set containing q elements taken from a larger set containing p elements. Let us remind that the number of q-subsets is given by the binomial coefficient $\binom{p}{q}$.

As mentioned in Section 2.1, the general idea is to decompose a p-class problem into a q_1-class sub-problem and a q_2-class sub-problem where $q_1 + q_2 = p$, and continuing recursively with the two sub-problems. Each decomposition relies on a binary classifier separating q_1 classes for the q_2 other ones. Thus, a tree of binary classifier is built. For classification, this tree has to be traversed from the root to a leaf, following a branch depending on the responses of the node classifiers. To optimize the classification complexity in terms of the number of classifiers that are tested, the tree must be of minimal depth or, equivalently, as close as possible to a perfect binary tree. This is achieved by enforcing the following constraints:

$$\left\{ \begin{array}{ll} q_1 + q_2 = p & \text{(partition constraint)} \\ |q_1 - q_2| \leq 1 & \text{(balance constraint)} \end{array} \right. . \quad (1)$$

The classification complexity is then equal to the tree depth, *i.e.* $\log_2(p)$. However, the limiting factor of such an approach is the combinatorial learning complexity in terms of the number of binary classifiers that must be determined at each node of the tree. Section 3 proposes another strategy involving graph theory in order to overcome this issue.

3 PROPOSED METHOD: GRAPH CUT BASED SVM TREE (GC-SVM)

3.1 Trade-off between Learning and Classification Complexities

The following description is valid for any binary classifier framework. However, this paper focuses on the SVM example. First, similarly to the one-versus-one approach, we compute the SVMs between each pair of classes among the $p \geq 3$ predefined classes. Now, following the recursive strategy described in Sections 2.2 and 2.1, let us assume that we are about to deal with a node containing more than three classes (originally, the root node contains all p classes).

The idea is to use graph theory tools to determine a bi-partition of this set of classes. This bi-partition will not necessarily be balanced (*i.e.* the second condition of Eq. 1 will no longer be taken into account). A labeled, weighted, undirected, complete graph G is built such that:

- Each node represents a class (*i.e.*, node $i \equiv$ class i);
- The weight c_{ij} of the edge linking nodes i and j is equal to the inverse of the margin of the SVM computed between classes i and j, *i.e.*, $c_{ij} = \frac{\|w_{ij}\|}{2}$.

The minimum cut of G will result in a bi-partition of the nodes such that the sum of the weights of the edges cut is minimal. It is computed using Stoer-Wagner's min-cut algorithm (Stoer and Wagner, 1997). Thanks to the chosen graph definition, this will also correspond to separating the classes of pairs that have a large SVM margin. Hence, the two virtual classes, union of the classes on each side of the partition, will tend to have a large margin too. We just have to compute the corresponding SVM and assign it to the current node. Therefore, for the whole tree building, $p(p-1)/2$ SVMs are computed first, then additional SVMs are computed for each non-leaf tree node. There are $p-1$ such nodes. Actually, for the nodes that are parents of two leaves, the SVM needs not be computed since it corresponds to one of the SVMs first computed for each pair of classes. Therefore, there are at most $p-1$ additional SVMs to be computed. As a result, $O(p^2)$ SVMs are computed in total. The proposed learning method is described in algorithm 1. It calls the procedure MINCUT which is entirely defined in (Stoer and Wagner, 1997).

Once the tree T of SVMs and virtual classes has been built, the classification of a new image signature is simply performed by following a unique branch based on the successive decisions of the nodes' SVMs. The branch leaf contains the label of the identified predefined class. Figure 1 presents an instance of SVM tree for five classes labeled 1 to 5.

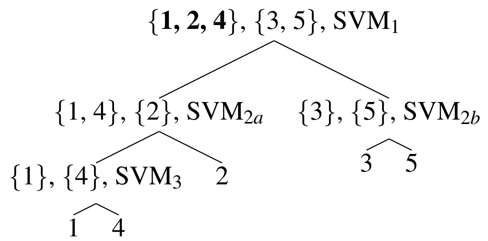


Figure 1: Type of tree that the proposed method builds during the learning stage. An example of classification of a new image signature is also illustrated by showing the visited nodes in boldface (read from root to leaf).

Algorithm 1: The GC-SVM algorithm.

```
procedure GCSVM(L, p)
    T ← empty tree
    if p == 1 then
        Create a node with label l_1 and add it to T
    else if p == 2 then
        Create two nodes with labels l_1 and l_2 and
add them to T
    else
        a ← an arbitrary node of G
        (L_1, L_2) = MINCUT(G, a)
        p_1 ← the number of classes in L_1
        p_2 ← the number of classes in L_2
        T_1 = GCSVM(L_1, p_1)
        T_2 = GCSVM(L_2, p_2)
        let T_1 be the left child of T
        let T_2 be the right child of T
    end if
    return T
end procedure
```

3.2 Complexity

Let us start with the learning step.

Proposition 1. *The number of SVM computed during the learning step is* $O(p^2)$.

Proof. The number of SVM computed is equal to the sum of:

- The number of binary SVM we compute to build the graph $O(p^2)$,
- The number of nodes in the graph built, *i.e.* $O(p)$.

As a result, the total number of SVM computed is $O(p^2)$. □

As for the classification step, the number of SVM used depends on the way the binary tree is built: it is equal to the depth of the tree. This is the reason why we distinguish the worst-case complexity and the best-case complexity.

Proposition 2 (Worst-case complexity for classification step)**.** *The worst-case complexity for the classification step is* $O(p)$.

Proof. The worst-case scenario happens when the tree built is a degenerate tree, *i.e.* when for each parent node, there is only one associated child node. In this case, the depth of the tree is $O(p)$. So is the complexity. □

Proposition 3 (Best-case complexity for classification step)**.** *The best-case complexity for the classification step is* $O(\log(p))$.

Proof. The best-case happens when the tree is balanced, *i.e.* when for each parent node, there are two associated child nodes whenever it is possible. In such a case, the depth is logarithmic, and as a result the complexity is $O(\log(p))$. □

Let us compare the methods above-mentionned with the most commonly used algorithms. Table 1 presents the complexities in terms of number of classes for both learning (offline task performed only once) and classification (performed on-demand), for one-versus-one, one-versus-all, the Directed Acyclic Graph SVM method (DAGSVM) (Platt et al., 2000), and the proposed methods.

The proposed method offers a lower classification complexity and still a reasonable learning complexity. Moreover, since testing a decomposition means learning a binary classifier, and since the computer time needed for a learning depends on the number of training samples, a straightforward way to reduce the learning time is to subsample cleverly the training set (Bakir et al., 2005).

4 EXPERIMENTAL RESULTS

The proposed method has been implemented in Matlab using the SVM-KM (Support Vector Machine and Kernel Methods) toolbox (Canu et al., 2005) which implements the binary SVM classifier as well as the one-versus-one and one-versus-all strategies. It has been applied to automatic classification of endomicroscopic videos.

The medical database to which we apply the classification methods contains 116 endomicroscopic videos, each of them showing a colonic polyp *in vivo* at the cellular level. These videos were acquired at the Mayo Clinic in Jacksonville during endoscopy procedures on 65 patients, using a technology called probe-based Confocal Laser Endomicroscopy (pCLE) developed by Mauna Kea Technologies. Each video is assigned to a pathological class which is the histological diagnosis established by an expert pathologist from a biopsy on the imaged polyp. The 5 pathological classes are: purely benign (14 videos), hyperplastic (21 videos), tubular adenoma (62 videos), tubulovillous adenoma (15 videos) and adenocarcinoma (4 videos) (See Fig. 2). In (André et al., 2011), a bag-of-visual-words method was proposed to build the visual signatures of these videos, based on mosaic images associated with stable video subsequences. To

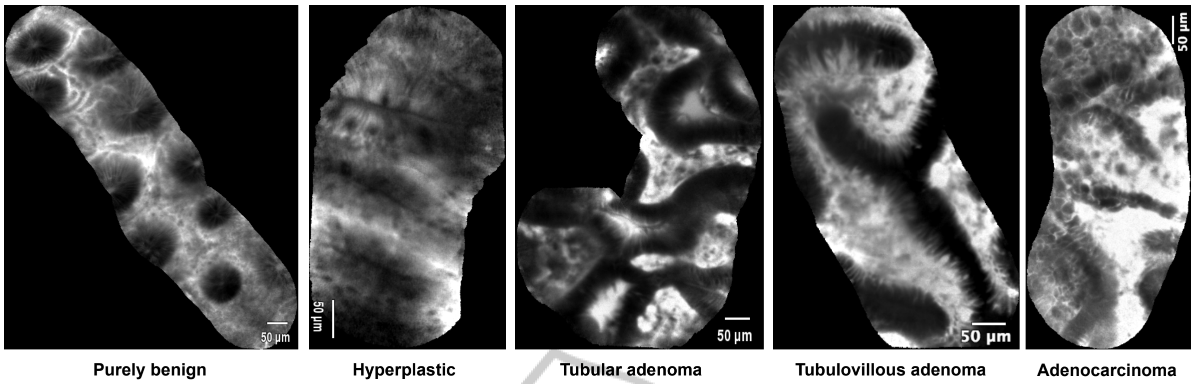
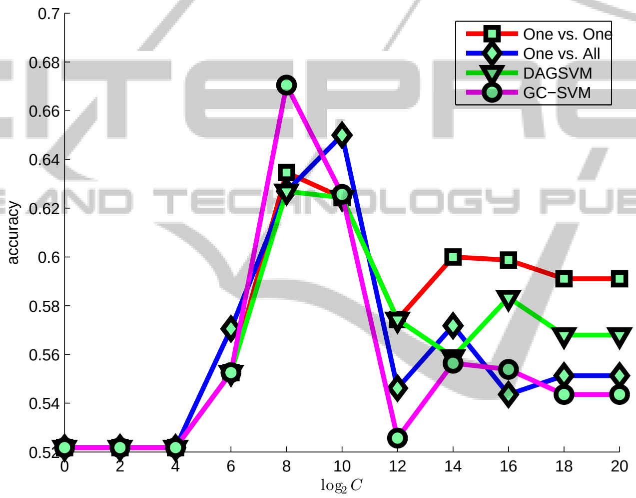
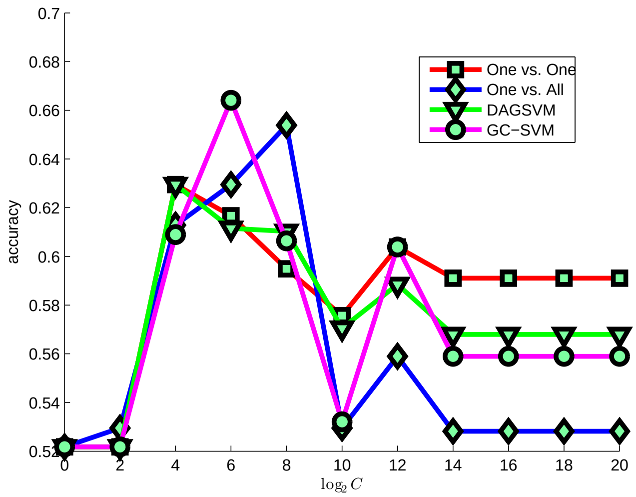


Figure 2: Examples of annotated endomicroscopic videos.



(a) Gaussian radial basis function kernel : $k(x_i, x_j) = \exp\left(\|x_i - x_j\|^2\right)$



(b) Polynomial kernel : $k(x_i, x_j) = \left(\langle x_i, x_j \rangle + 1\right)^2$

Figure 3: Accuracies (*vertical axis*) as functions of the parameter $\log_2(C)$ for one-versus-one, one-versus-all, DAGSVM, and the proposed methods. Let us remind that C is the soft margin parameter (see Section 1).

Table 1: Number of SVMs computed for p classes.

Method	Learning	Classification
One-versus-one	$O(p^2)$	$O(p^2)$
One-versus-all	$O(p)$	$O(p)$
DAGSVM	$O(p^2)$	$O(p)$
GC-SVM	$O(p^2)$	Between $O(\log_2(p))$ and $O(p)$

Table 2: Best average accuracies for the method (André et al., 2011) and the multiclass SVM methods with their own optimal value of C (see Fig. 3).

Method	Best accuracy
(André et al., 2011) with adapted signatures	62.9%
One-versus-one	63.5%
One-versus-all	65.0%
DAGSVM	62.7%
GC-SVM (proposed)	**67.1%**

make the videos signatures easily exploitable without learning bias, we adapted this signature extraction method by considering as visual words 100 description vectors randomly selected in 5 endomicroscopic videos of colonic polyps that do not belong to the database. Because the size of the database is relatively small, the classification methods were applied to the adapted video signatures using leave-one-patient-out cross validation (André et al., 2011). For multiclass classification method comparison, we added, as reference method for endomicroscopic video classification, the k-Nearest Neighbors (k-NN) classification method of (André et al., 2011) that uses a weighted majority vote based on the χ^2 similarity distance between the adapted video signatures. The video classification results are given in Fig. 3 and Table 2.

In this experiment, the proposed method performs the best despite having a lower classification complexity. On Fig 3, it can be noted that the range of good values for the parameter C is roughly the same for all four SVM-based methods. However, above this range, the accuracy significantly drops for all the methods.

5 CONCLUSION AND PERSPECTIVES

The results of Section 4 are encouraging since the classification of the GC-SVM algorithm slightly outperforms the standard methods on our dataset, while having a lower classification complexity (see Table 1). However, as shown in Figure 3, the accuracy of the classification depends on various parameters:

- The choice of the kernel,
- The parameters defining the kernel (degree of the polynomial, variance of the Gaussian radial basis function, ...),
- The soft margin parameter, C.

This issue affects all the multiclass SVM methods stated in this paper. In most cases, the choice of the kernel and its parameters is left to the user or computed through a cross validation. The kernel and its parameters could either be computed automatically or learned (Cortes et al., 2008) to avoid a cross validation.

Another perspective which could be taken into account is to change the capacity c of the min-cut algorithm (Stoer and Wagner, 1997). As a matter of fact, we could try to have the binary tree built by the GCSVM algorithm as balanced as possible in order to lower its depth and consequently the number of SVM used during the classification step (see Section 3.2). This can be done by defining an energy term e equal to the sum of the capacity c and an "imbalance term" as suggested in (Dell'Amico and Trubian, 1998). If The cut of the graph is $(A,\bar{A})$, then a possible definition of this energy term could be

$$e(A,\bar{A}) = c(A,\bar{A}) + \lambda\big||A| - |\bar{A}|\big|$$

where λ is the "imbalance factor", which depends on how hard we want the tree to be balanced.

Finally, the method should be tested on bigger data sets, particularly composed of more classes, in order to better evaluate the performance gain compared to methods with linear and quadratic complexities.

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