Multiclass $m\nu$-Granular Soft Support Vector Machine: A Case Study in Dynamic Classifier Selection for Multispectral Face Recognition

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Abstract

This paper presents a novel formulation of multiclass support vector machine by integrating the concepts of soft labels and granular computing. The proposed multiclass $m\nu$-granular soft support vector machine uses soft labels to address the issues due to noisy and incorrectly labeled data, and granular computing to make it adaptable to data distributions both globally and locally. The proposed multiclass classifier is used for dynamic selection in a multispectral face recognition application. Specifically, for the given probe face images, $m\nu$-GSSVM is used to optimally choose one of the four options: visible spectrum face recognition, short-wave infrared face recognition, multispectral face image fusion, and multispectral match score fusion. Experimental results on a multispectral face database show that the proposed algorithm improves the verification accuracy and also decreases the computational time.

1. Introduction

Support Vector Machine (SVM) is a powerful optimal margin linear discriminant used for binary data classification [8]. Several researchers have proposed extensions of SVM for m-class classification. However, these algorithms are computationally complex and optimized for particular applications [3]. This paper presents a novel multiclass SVM classification approach to address the limitations of existing approaches. *The novelty of the proposed multiclass $m\nu$-Granular Soft Support Vector Machine ($m\nu$-GSSVM) is integrating the concept of soft labels and granular computing into SVM to reduce the training complexity and increase the classification performance*.

The proposed $m\nu$-GSSVM algorithm is used for dynamic classifier selection in multispectral (visible and short wave infrared spectrum) face recognition. This paper also introduces the use of learning approach to dynamically select the most appropriate unimodal classifier or fusion algorithm for a given face image. Experiments on a multispectral face database show that the proposed algorithm improves the face verification accuracy without increasing the computational time.

2. Formulation of Multiclass $m\nu$-GSSVM

For a binary classification problem, let $\{\mathbf{x}_i, y_i\}$ be a set of N data vectors where $\mathbf{x}_i \in \Re^d,\ y_i \in (+1, -1)$ is the hard label, and $i = 1, ..., N$. The basic principle behind dual ν-SVM (2ν-SVM) [2], which is a computationally efficient variant of SVM, is to find the widest margin, i.e., $\mathbf{w}\varphi(\mathbf{x}) + b = 0$ such that,

$$\begin{array}{l} \text{minimize: } \frac{1}{2}\|\mathbf{w}\|^2 - \sum_i C_i(\nu\rho - \psi_i) \\ \text{subject to: } y_i\left(\mathbf{w}\,\varphi(\mathbf{x}_i) + b\right) \geq (\rho - \psi_i) \end{array} \tag{1}$$

where $\mathbf{w}$ is the normal weight vector, $\varphi(\mathbf{x})$ is the mapping function used to map the data space to the feature space and provide generalization for the decision function. $\rho \geq 0$ is the position of the margin, ν is the error parameter, $C_i(\nu\rho - \psi_i)$ is the cost of errors, b is the bias, C_i is the error penalty, and $\psi_i \geq 0$ is the slack variable for classification errors. 2ν-SVM objective function can be formulated as (Wolfe Dual formulation),

$$L = \sum_i \alpha_i - \frac{1}{2}\sum_{i,j} \alpha_i\,\alpha_j\,y_i\,y_j\,K(x_i, x_j) \tag{2}$$

where $i, j \in 1, ..., N$, $K(\mathbf{x}_i, \mathbf{x}_j)$ is the kernel function [8], α_i, α_j are the Lagrange multipliers such that $0 \leq \alpha_i \leq C_i$, $\sum_i \alpha_i y_i = 0$, and $\sum_i \alpha_i \geq \nu$.

Sometimes, the 2ν-SVM performs erroneous classification due to incorrect training data that are either noisy or incorrectly labeled. To address this limitation, we extend the formulation of 2ν-SVM with soft labels [7]. The soft labels can reduce the classification error and decrease the number of support vectors required.

Let z_i be the soft label for the i^{th} training data x_i such that $z_i = 2p(\cdot|x_i) - 1$ where $p(\cdot|x_i)$ is the posterior probability which is calculated using a k-NN estimator. For the m^{th} class, $p(m|x) = \frac{k_m}{k}$, where k_m is the number of training data among k nearest neighbors. Using the soft labels, 2ν-SVM is transformed into 2ν-Soft SVM (2ν-SSVM), i.e.,

$$\begin{array}{l} \text{minimize: } \left\{\frac{1}{2}\|\mathbf{w}\|^2 - \sum_i C_i(\nu\rho - \psi_i)\right\} \\ \text{subject to: } z_i\left(\mathbf{w}\,\varphi(\mathbf{x}_i) + b\right) \geq z_i^2(\rho - \psi_i) \end{array} \quad (3)$$

We next integrate the concept of granular computing [1] in 2ν-SSVM to increase the data distribution adaptive capability both locally and globally and propose 2ν-Granular SSVM (2ν-GSSVM). Let the data space be divided into c subspaces with one 2ν-SSVM operating on each subspace. Let $2\nu\mathrm{SSVM}_i$ represent the i^{th} 2ν-SSVM and $2\nu\mathrm{SSVM}_i :\rightarrow L_i$ represent the 2ν-SSVM operating on the i^{th} subspace ($i = 1, ..., c$). The compound margin width W is computed as follows:

$$W = \left| \sum_{i=1}^{c} \frac{t_i}{t}(2\nu SSVM_i :\rightarrow L_i) - L_0 \right| \quad (4)$$

where $t = \sum_{i=1}^{c} t_i$ and t_i is the number of training data in the i^{th} subspace. 2ν-SSVM learning yields L_i at the local level and L_0 is obtained by learning another 2ν-SSVM on the complete feature space at global level. This equation provides the margin width associated with 2ν-GSSVM hyperplane.

The formulation of 2ν-GSSVM is for binary classification problem. In literature, there are several approaches [3] to extend the formulation for m-class classification such as single multiclass machine (SMM), One-Against-All (OAA), One-Against-One (OAO), Directed Acyclic Graph (DAG), and Half-Against-Half (HAH). Any of these approaches can be used to extend the proposed 2ν-GSSVM to a multiclass $m\nu$-GSSVM. For any of the above mentioned multiclass classification approaches, the error parameters ν and C can be calculated using Equation (5) and Equation (6) respectively.

$$\nu = \frac{m\prod_{j=1}^{m}\nu_m}{\sum_{j=1}^{m}\nu_m}, \;\; 0 < \nu_m = \frac{n_m}{N} < 1 \quad (5)$$

$$C_m = \left[n_m \left(1 + \frac{\nu_m}{\sum_{j=1, j\neq m}^{m}\nu_j} \right) \right]^{-1} \quad (6)$$

where n_m is the number of training points for the m^{th} class. The proposed multiclass $m\nu$-GSSVM can be used for any classification problem. In this paper, we use it for dynamic classifier selection to improve the performance of multispectral face recognition.

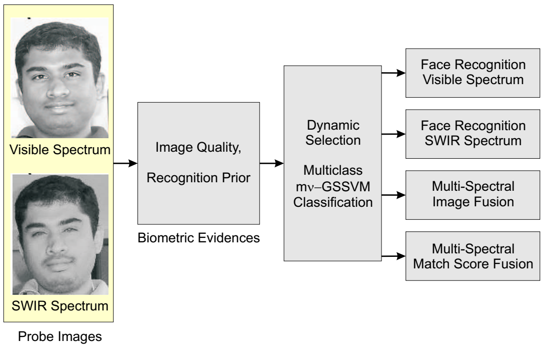
3. Dynamic Classifier Selection for Multispectral Face Recognition

The real world operating conditions may yield nonideal face images, making the task of face recognition very challenging. To address the limitations of current face recognition algorithms, researchers have proposed the use of short wave infra-red (SWIR) images. However, there are several limitations of using only SWIR spectrum such as problem due to glasses or outdoor illumination. The Pearson's correlation between match scores obtained from texture feature based face recognition algorithm [5] applied on both visible and SWIR spectrum images suggest that there is limited correlation between the match scores of these two spectrums. Therefore, it is possible to improve the verification accuracy by combining the information obtained from both visible and SWIR spectrum. Information fusion techniques [4] such as image fusion and score fusion [6] have been proposed to compensate for the inadequacies of both visible and SWIR spectrum images. However, Pearson's correlation analysis between image fusion and match score fusion suggests that the unification of fusion algorithms can further improve the verification accuracy. One way to reconcile the multilevel fusion algorithms is to combine them hierarchically [6] but the hierarchical approach is computationally expensive. Further, if the probe image is of high quality and exhibits sufficient facial information useful for recognition then fusion may not be necessary.

Another way to improve the verification accuracy without increasing the computational cost is to develop a case based approach that dynamically selects the most appropriate classifier or fusion algorithm for given multispectral probe images. In our previous research [9], we proposed a contextual unification framework using deterministic rules to dynamically select the most appropriate match score fusion algorithm for a given scenario. In this paper, we extend the unification framework to face recognition by incorporating the proposed $m\nu$-GSSVM classification, unimodal classifiers, image fusion, and match score fusion. As shown in Figure 1, the dynamic selection algorithm uses multiclass $m\nu$-GSSVM to select one of the four options: (1) only visible spectrum face recognition, (2) only SWIR spectrum face recognition, (3) visible and SWIR image fusion, and (4) visible and SWIR match score fusion. The selected algorithm is then used for final decision-making. The evidences which serve as input to the framework are image quality score and recognition prior.

The first step in the proposed dynamic classifier selection algorithm is to compute the image quality score of input multispectral face images. The redundant dis-

Figure 1. Block diagram of the proposed dynamic classifier selection framework.



crete wavelet transform based image quality assessment algorithm [10] is applied locally on the face image in blocks of 16×16. For each face block, the algorithm quantifies the intrinsic physical content and environmental dynamics such as illumination, noise, and blur. The image quality score Q is a vector in which each element is a normalized score (in the range of [0,1] where 0 belongs to worst quality and 1 belongs to best quality) pertaining to one block. Image quality vectors of the visible and SWIR spectrum face images along with the recognition priors are used as input to the $m\nu$-GSSVM classifier. The classifier is then trained using the labeled training data and *$m\nu$-GSSVM Training* algorithm to perform dynamic classifier selection for the input probe images. Labeling is performed using the density estimation [11] approach. Likelihood ratio $P_l = \frac{g_{good}(r_l,Q_t)}{g_{bad}(r_l,Q_t)}$ is computed where r represents the recognition prior, l belongs to the four options, t represents the multispectral images, and g represents the joint marginal densities of good and bad quality. Soft label is assigned as the highest P value among four options.

$m\nu$-GSSVM Training: A labeled training database is used to train the $m\nu$-GSSVM for dynamic classifier selection.

1. Let the input training data be $\{\mathbf{x}_i, z_i\}$ where $i = 1, ..., N$ and N is the total number of training samples. $\mathbf{x}_i$ is the i^{th} data vector and is composed of multispectral image quality vectors and recognition priors. z_i is the soft class label that provides information about the optimal algorithm.

2. $m\nu$-GSSVM is trained using radial basis function (RBF) kernel ($= exp(-\gamma||\mathbf{x}_i - \mathbf{x}_j||^2)$). The output of the trained $m\nu$-GSSVM is a multiclass nonlinear decision hyperplane.

Dynamic Selection: At the probe level, the trained $m\nu$-GSSVM is used to dynamically select the most appropriate algorithm depending on the image quality scores and recognition priors.

1. The image quality vectors and recognition priors pertaining to both the probe images are provided as input to the mixture model and trained $m\nu$-GSSVM. The classification algorithm selects one of the four options: recognition using visible spectrum only, recognition using SWIR spectrum only, recognition at image fusion level, and recognition at match score fusion level.

2. Depending on the classification result of the $m\nu$-GSSVM classifier, the selected option is used to compute a decision of accept or reject.

3.1 Experimental Evaluation

To evaluate the performance of the proposed $m\nu$-GSSVM based dynamic classifier selection algorithm, we use the Equinox face database[1] that contains visible and SWIR spectrum face images. This database is augmented with the multispectral face images captured at West Virginia University. The multispectral database contains face images from 135 individuals with 7-25 images per subject. We follow a widely used experimental protocol in which the images are partitioned into two sets: (1) training and (2) gallery-probe datasets. For training, three images of each spectrum are randomly selected from each subject. The remaining images are used as the test data to evaluate the algorithms. This train-test partitioning is repeated 25 times (cross validation) and ROC curves are generated. Furthermore, verification accuracies are reported at 0.01% false accept rate (FAR). For evaluation, texture based algorithm [5] is used for multispectral face recognition, and image fusion and match score fusion algorithms described in [6] are used for the fusion framework. Hierarchical fusion algorithm [6] is used for performance comparison.

Different multiclass classification approaches such as SMM, OAO, OAA, DAG, and HAH are experimentally evaluated using the training dataset and RBF kernel. We observed that the HAH approach for $m\nu$-GSSVM with RBF parameter $\gamma = 4$ and k-NN estimator parameter $k = 7$ yields the best performance with 99.3% accuracy and takes only 0.48 seconds[2] for verification whereas other multiclass classification approaches yield 97.6-99.2% accuracy with computational time of 1-2 seconds. The proposed multiclass $m\nu$-GSSVM also outperforms existing multiclass

[1] http://www.equinoxsensors.com/products/HID.html

[2] Time is computed on a PC with 3.2 GHz P-IV processor and 2 GB RAM under MATLAB environment

Figure 2. Performance evaluation using ROC curves.

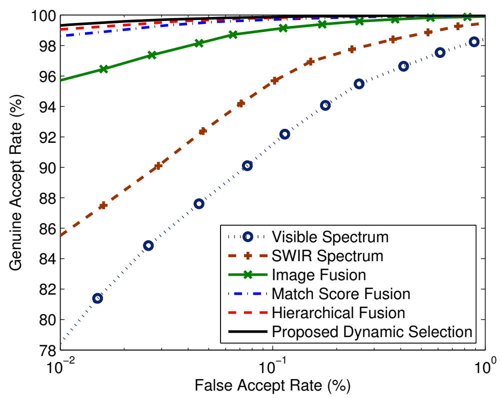


Table 1. Comparison of the proposed dynamic classifier selection algorithm with existing fusion algorithms.

	Accuracy		Time
	Average	Range	(sec.)
Visible Spectrum	78.5	74.2 - 83.9	1.45
SWIR Spectrum	85.6	82.7 - 88.3	1.45
Image Fusion	95.8	94.1 - 96.5	3.76
Score Fusion	98.6	97.9 - 99.8	3.68
Hierarchical Fusion	99.1	98.2 - 99.9	4.42
Dynamic Selection	99.3	99.0 - 100	2.94

canonical SVM approaches [3] both in terms of accuracy and speed. Therefore, remaining experiments on the gallery-probe dataset are performed using the trained $m\nu$-GSSVM with the HAH approach. The ROC plots for the multispectral face images (Figure 2) show that the SWIR spectrum face images provide 7.1% better accuracy than the visible spectrum face images. Figure 2 also shows that the use of fusion algorithms improves the verification accuracy by at least 10.2-13.7%. However, as shown in Table 1, existing multispectral fusion algorithms increase the computational time. Furthermore, with different cross validation trials, the accuracy range shows that the proposed $m\nu$-GSSVM based dynamic selection algorithm is the most stable algorithm. The experiments establish that the proposed dynamic selection algorithm is computationally efficient. Also, more than 99% verification accuracy shows that the algorithm is able to compensate for the variations in expression, pose, illumination, and occlusion. Finally, t-test statistics suggests that at 95% confidence, the proposed algorithm is significantly different than existing fusion algorithms.

4. Conclusion

The contribution of this research is two fold: (1) the formulation of multiclass $m\nu$-granular soft support vector machine and (2) dynamic classifier selection algorithm for choosing the optimal unimodal classifier or fusion algorithm to improve the multispectral face recognition performance. The proposed $m\nu$-GSSVM incorporates the fundamentals of granular computing and soft labels to efficiently solve the multiclass classification problem. The case study on multispectral face recognition shows that the proposed $m\nu$-GSSVM is efficient for dynamic classifier selection both in terms of accuracy and speed.

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