I.J. Engineering and Manufacturing **2011, 3, 69-74**
Published Online June 2011 in MECS (http://www.mecs-press.net)
DOI: 10.5815/ijem.2011.03.11

Available online at http://www.mecs-press.net/ijem

Pain Expression Recognition Based on SLPP and MKSVM

Zhang Wei, Xia Li-min

College of Information Science and Engineering, Central South University, Changsha 410075, China

Abstract

In this paper, a novel approach is proposed for recognizing pain expression. First of all, supervised locality preserving projections (SLPP) is adopted for extracting feature of pain expression, which can solve the problem that LPP ignores the within-class local structure using adopting prior class label information, and then multiple kernels support vector machines (MKSVM) is employed for recognizing pain expression, Compared to SVM, which can improve the interpretability of decision function and classifier performance. Experimental results are shown to demonstrate the effectiveness of the proposed method.

Index Terms: Pain expression recognition; SLPP; MKSVM

1. Introduction

Pain is difficult to assess and manage. Pain is fundamentally subjective and is typically measured by patient self-report, either through clinical interview or visual analog scale (VAS). This techniques are popular because they are convenient. simple, satisfy. Self-report measures, however, have several limitations. These include idiosyncratic use, inconsistent metric properties across scale dimensions, reactivity to suggestion, efforts at impression management or deception, and differ-ences between clinician's and sufferers' conceptualization of pain. Moreover, self-report measures cannot be used with young children, with many patients in postoperative care or transient states of consciousness, and with severe disorders requiring assisted breathing, among other conditions [1,2].

In the past several years, significant progress has been made in machine learning to automatically recognize pain expressions. In [2], An approach was developed to automatically recognize acute pain, Active Appearance Models (AAM) was used to decouple shape and appearance parameters from face images, Based on AAM, three pain representations were derived. And then SVM were used to classify pain. In [3], a robust approach for pain expression recognition was presented using video sequences. Pain expression recognition is performed by projecting a new image onto the feature spaces spanned by the Eigenfaces and then classifying the painful face by comparing its position in the feature spaces with the positions of known individuals.

* Corresponding author.
E-mail address: 360706711@qq.com,xlm@mail.csu.edu.cn

In this paper, we develop a novel approach to recognize acute pain. This approach includes two steps: extracting feature of pain expression and classifying pain expression. In the extracting feature, features of pain expression are extracted by supervised locality preserving projections in face-images [4]. Then we use multiple kernels SVM to classify with several representations from priority step [5]. Our approach can enhance the accuracy of recognizing pain expression using two improvements. (1) SLPP can solve the problem which LPP ignores within-class local structure with prior class label information. (2)Compared with a single one multiple kernels learning, using multiple kernels can enhance interpretability of the decision function and improve classifier performance.

2. Pain feature extraction

We propose supervised locality preserving projections (SLPP), which solve the problem which LPP ignores the within-class local structure using adopting prior class label information, and use SLPP to extract pain feature from face images.

A. Locality Preserving Projections

Locality preserving projection (LPP) [6] is a recently proposed dimensionality reduction method, which can try to find a transformation matrix A to project high-dimensional input data $X = [x_1, x_2, ..., x_n]$ into a low-dimensional subspace Y in which the local structure of the input data can be preserved. The objective function of LPP is as follows:

$$\min_A \sum_{i,j=1}^{n} \left\| y_i - y_j \right\|^2 S(i,j) \tag{1}$$

where

$$y_i = A^T x_i \text{ , } W_{ij} = \begin{cases} 1 & x_i \textit{ is among K nearest neighbors of } x_j \\ 0 & \text{otherwise} \end{cases} .$$

The minimization problem can be converted to solving a generalized eigenvalue problem as follows:

$$XLX^T a = \lambda XDX^T a \tag{2}$$

where $D_{ij} = \sum_j S(i,j)$ is a diagonal matrix, and $L = D - S$.

Let the column vectors $a_0, a_1, ..., a_{d-1}$ be the solutions of (2)ordered according to their eigenvalues $\lambda_0, \lambda_1, ..., \lambda_{d-1}$, Thus, the embedding is as follows:

$$x_i \to y_i = A^T x_i, A = [a_0, a_1, ..., a_{d-1}] \tag{3}$$

where y_i is a d-dimensional vector, and A is a $N \times d$ matrix.

B. Pain Feature Extraction Based on S lPP

LPP fail to deliver good performance when the data structure is nonlinear because they are intrinsically linear. In addition, it ignores the within-class local structure, which may sometimes make them unsuitable for object recognition. With prior class label information, we propose a supervised approach for pain feature extraction, i.e., supervised locality preserving projections. Assuming a set of face images $X = [(S_1, C_1), (S_2, C_2), ..., (S_n, C_n)]$, where $S_i = [x_1, x_2, ..., x_m)]$ is a face image which have N-dimensional features, and C_i is been regard as a class label. Similarly to [7], we use a nonlinear function ϕ to map the data into a high-dimensional feature space $F : \phi(X) = [\phi(x_1), \phi(x_2), ..., \phi(x_n)]$ .Then in feature space F , we seek a projecting transformation P that can preserve the within-class geometric structure of the data $\phi(x)$ by minimizing the sum of the weighted distance of samples. The minimization problem can be expressed as

$$\min_{P} \sum_{i,j=1}^{m} \left\| z_i - z_j \right\|^2 W(i,j) \tag{4}$$

$W_{ij} = \begin{cases} \phi(x_i)\cdot\phi(x_j) & x_i \; and \; x_j \; belong \; to \; the \; same \; label \\ 0 & \text{otherwise} \end{cases}$, $z_i = P^T \phi(x_i)$,. Each entry of the weight matrix W can be regarded as the similarity metric of a pair of samples with class label information. The objective function can be simplified as

$$\sum_{i,j=1}^{n} \left\| z_i - z_j \right\|^2 W(i,j) == 2P^T \phi(X)(D-W)\phi^T(X)P \tag{5}$$

where $D_{ii} = \sum_j W(i,j)$ is a diagonal matrix. Because the linear transformation P should lie in the span $\phi(x_1), \phi(x_2), ...\phi(x_n)$, of there exists a coefficient vector $a = [a_1, a_2, ...a_n]$, such that

$$P = \sum_{i=1}^{n} a_i \phi(x_i) = \phi(X)a \tag{6}$$

Substituting (6) into (5), we can obtain

$$\sum_{i,j=1}^{n} \left\| z_i - z_j \right\|^2 W(i,j) == 2a^T K(D-W)Ka \tag{7}$$

where the matrix $K(i,j) = \phi(x_i)\cdot\phi(x_j)$ .Thus, this minimization problem can be converted to a generalized eigenvalue problem with a constraint condition $a^T KDKa = 1$. The eigenvectors corresponding to the smallest eigenvalues are the solution

$$K(D-W)Ka = \lambda KDXa \tag{8}$$

Projecting transformation P can be solved according to (8) and (6). Thus, features of pain expression $z = (z_1, z_2 ... z_m)$ are calculated as follows:

$$z = P^T \phi(x) \tag{9}$$

3. Pain expression recognition

Support Vector Machines are a family of pattern classification algorithms , which are often been used to classify faces with a single kernel Meanwhile, in this paper, multiple kernel learning using multiple kernels instead of a single one is used to recognite pain, which can enhance interpretability of the decision function and improve classifier performance.

C. Support Vector Machine

Support Vector Machines [8] are based on the idea of structural risk minimization rather than empirical risk minimization. Assume that we have a data set $D=\{x_i, y_i\}_{i=1}^{m}$ of labeled examples, where $x_i \in X$ is the input vector, and $y_i \in \{-1,1\}$. Introducing a feature mapping ψ from the input space X to a reproducing kernel Hilbert space (RKHS) H , linear classifiers in H of the form

$$f(x) = w^T \phi(x) + b \ . \tag{10}$$

The parameters (w,b) are determined by solving the optimization problem

$$\begin{aligned} &\min_{w,b,\xi} \frac{1}{2}\|w\|_2^2 + C\sum_{i=1}^{n}\xi_i, \\ &s.t.\ \forall i,\ y_i\left\{w^T\phi(x_i)+b\right\} \geq 1-\xi_i;\ \xi_i \geq 0 \end{aligned} \ . \tag{11}$$

where $\|\cdot\|_2$ denotes the l_2 norm and C>0 is a regularization constant. The above formulation into the equivalent dual optimization problem prevents from dealing with features in H explicitly.

$$\begin{aligned} &\min_{\alpha} \sum_{i=1}^{n}\alpha_i - \frac{1}{2}\sum_{i,j=1}^{n}\alpha_i\alpha_j y_i y_j k(x_i, x_j) \\ &s.t.\ 0 \leq \alpha_i \leq C, \forall i; \sum_{i=1}^{n} y_i\alpha_i = 0 \end{aligned} \ . \tag{12}$$

where $k(x, x_i) = \langle \phi(x), \phi(x_i) \rangle$. Once, optimal parameters are found, these are used as plug in estimates and the final decision function can be written as

$$f(x) = \sum_{i=1}^{n}\alpha_i k(x_i, x) + b \ . \tag{13}$$

D. Pain Expression Recognition Based on MKSVM

In the above kernel method, the data representation is implicitly chosen through the kernel function $k(x_i, x)$. However, it is often unclear what the most suitable kernel for the task at hand is, and hence we wish to combine several possible kernels. The multiple kernel learning can be used for training multiple kernels by jointly optimizing both the coefficients of the classifiers and the weights of the kernels, which have a more excellent effectiveness for object recognition than SVM [9, 10].

Let $K_1, K_2, \ldots, K_m$ be m kernel matrices with $K_t = [k_t(x_i, x_j)]_{i,j=1,\ldots,n}$ obtained from different sources or features. The multiple kernel learning framework extends the regular SVM formulation by additionally learning a linear mixture of the kernels, i.e.

$$K_\beta = \sum_{i=1}^{m} \beta_i K_i \ . \tag{14}$$

Thus, the model in (10) is extended to

$$f(x) = \sum_{i=1}^{n} \beta_i w_i^T \phi_j(x) + b \ . \tag{15}$$

The corresponding optimization problem maximizes the generalization performance by simultaneously optimizing the parameters w , b , ξ and β . We obtain the common l_1 norm

$$\begin{aligned} &\min_{\beta,w,b,\xi} \frac{1}{2}\|w\|_2^2 + C\sum_{i=1}^{n}\xi_i \\ &s.t.\ \forall i,\ y_i\left\{\langle w,\phi(x_i)\rangle + b\right\} \ge 1-\xi_i \ . \\ &\quad \xi \ge 0,\ \beta \ge 0,\ \|\beta\| \le 1 \end{aligned} \tag{16}$$

where $\phi(x_i) = \left(\sqrt{\beta_1}\phi_1(x_i),\ldots,\sqrt{\beta_m}\phi_m(x_i)\right)^T$, $w = \left(\sqrt{\beta_1}w_1,\ldots,\sqrt{\beta_m}w_m\right)^T$. The above optimization problems can be translated into a semi-infinite program, and we can solve the above optimization problems with standard techniques [11]. Note that the above optimization problem is the regular SVM optimization problem when m=1.

In the pain expression recognization, the feature of pain expression $z = (z_1, z_2 \ldots z_m)$ is used as input of multiple kernel SVM. Output of multiple kernel SVM is $y_i \in \{-1,1\}$, and -1 means normal mood, and 1 means pain mood.

4. Experimental results and analysis

We have used a database of painful and normal face images. In this database, there are two groups of images and each group includes 22 males and 20 females. The first group is normal mood, and the second group is in painful mood. The images were taken under various laboratory-controlled lighting conditions. 32 face images per class are randomly chosen for training, while the remaining images are used for testing. We pre-processed these images by aligning and scaling them so that the distances between the eyes were the same for all images and also ensuring that the eyes occurred in the same coordinates of the image. Sample images are shown in Fig.1.We run the system 5 times and obtain 5 different training and testing sample sets. The recognition rates were found by averaging the recognition rate of each run

Fig.1:Examples of face images. Top row: Pain; Bottom row: No Pain

Table.1 Comparison of two detection methods

Method	EER	Correct rate
Proposed met	0.0945	0.9055
Method in[2]	0.1879	0.8121

To examine the accuracy of our proposed pain recognition system, we have tested our system several times. 68 different expression images are used for this experiment. Some images contain the same person but in different mood. As shown in table.1, our algorithm shows good results, with precision over 90%. The correct rate is 9% higher than the results from paper [2].The reason is that we improve the recognition accuracy in the two stages of pain feature extraction and expression recognition. In the stage of pain feature extraction, we use supervised locality preserving projections to extract face feature. In the stage of expression recognition, we use multiple kernels SVM to classify expression images.

5. Conclusions

In this paper, we present a novel machine learning method to recognize the pain expression. Our work focuses on two places. (1)In extracting feature, improved LPP, SLPP is used to extract features of pain expression with propriety information, which makes it possible to avoid the problem which LPP ignores within-class local structure. (2)We used MKSVM to recognite pain expression, Compared with a single one, multiple kernels learning using multiple kernels can enhance interpretability of the decision function and improve classifier performance. Finally, the experiment's results can prove that our approach enhance the accuracy of recognizing pain expression.

References

[1] K. D. Craig, K. M. Prkachin, and R. V. E. Grunau. The facial expression of pain. In D. C. Turk and R. M., editors, Handbook of pain assessment. Guilford, New York, 2nd edition, 2001.

[2] A.B. Ashraf, Simon Lucey, T. Chen. The Painful Face–Pain Expression Recognition Using Active Appearance Models. Cohn Proceedings of the ACM International Conference on Multimodal Interfaces, 2007, pp. 9 - 14.

[3] Md. Maruf Monwar, Siamak Rezaei and Dr. Ken Prkachin. Eigenimage Based Pain Expression Recognition, IAENG International Journal of Applied Mathematics, 36:2, IJAM_36_2_1, 2007.

[4] Xiao yong liang,Xia limin. Shot boundary detection based on supervised locality preserving projections and KNN-SVM classifier, CAR 2010 - 2010 2nd International Asia Conference on Informatics in Control, Automation and Robotics, v 1, p 341-344, 2010.

[5] Xiao yong liang,Xia limin. Face recognition with supervised spectral regression and multiple kernel SVM, Proceedings - 2nd IEEE International Conference on Advanced Computer Control, ICACC 2010, v 4, p 343-346, 2010。

[6] He X F, Niyogi P, Locality preserving projections. In: Proceeding of Neural Information Processing Systems, Vancouver, Canada, 2003, pp.153-160.

[7] Xuelian Y, Xuegang W, Benyong L.Supervised kernel neighborhood preserving projections for radar target recognition, *Signal Processing* , 2008, pp. 2335-2339

[8] B Schölkopf, A J Smola. Learning with Kernels: Support Vector Machines Regularization, Optimization and Beyond. *Cambridge, USA: MIT Press*, 2002, pp. 34-41.

[9] A Vedaldi, V Gulshan, M Varma, et al. Multiple kernels for object detection. *In Proc. ICCV*, 2009.

[10] S Y Fu, Z G Hou, Z Z Liang, et al. Multiple kernel learning from sets of partially matching image features. *In Proc. ICPR*, 2008

[11] P F Felzenszwalb, D McAllister, D Ramanan. A discriminatively trained, multiscale, deformable part model. *In Proc. CVPR,* 2008, pp.1-8.