International Journal of Science and Research (IJSR)
ISSN (Online): 2319-7064
Impact Factor (2012): 3.358

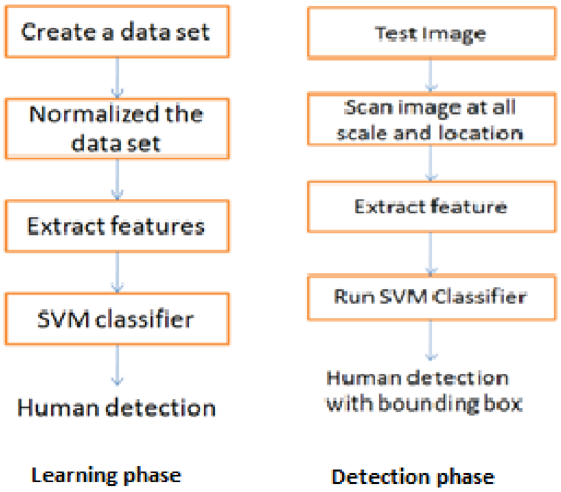

Figure 6: Learning and detection phase

5. Strength of N-linear SVM

With one SVM classifier line two classes can be classified, with two SVM classifier line three classes can be classified and similarly for three SVM classifier line four classes can be classified as shown in figure 7.

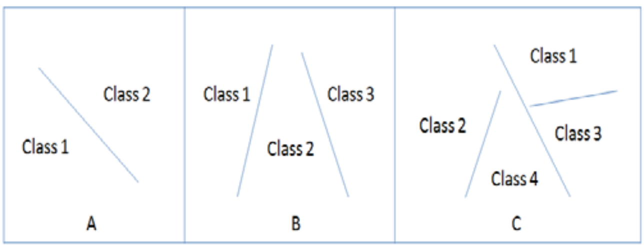

Figure 7: A- shows 1 SVM 2 classes, B- shows 2 SVM 3 classes and C- shows 3 SVM 4 classes

The figure 7 shows the number of SVM used and the number of classes it classify. It shows the representation of different SVM classifier lines for linearly classifiable and linearly separable data. As the number of classifier increased the power of classification also increased with it. This technique is used for classifying the human posture in an image file. With the N-linear SVM, N number of SVM classifier line can be drawn to classify human figure. This N number of classifier line is represented as non linear classification boundary. Thus using a linear SVM a non linear classification boundaries are obtained. Thus the classifier produces a non-linear classifier boundary around human posture utilizing the power of N-linear SVM. The SVM classifier lines are produce around the pose of person, which can be represented as drawing the SVM classifier line around the polygon, as shown in figure 8.

The points (1,2,3,a) and (4,5,6,7,b) forms a positive convex polygon which shows the promising result for human posture parts and rest of the part is represented with negative polygon. The nearest point (a,a') and (b.b') are used to classify the SVM line with a large classification margin. In [A32] it is shown that the problem of finding the maximum margin in SVM is same as the problem of finding the nearest point problem (NPP). It shows that SVM problem can be easily transferred to the problem of finding nearest point between two convex polytopes. By applying this idea N-linear classifier are utilized to construct the non linear classification margin around polytopes, in this case a human posture.

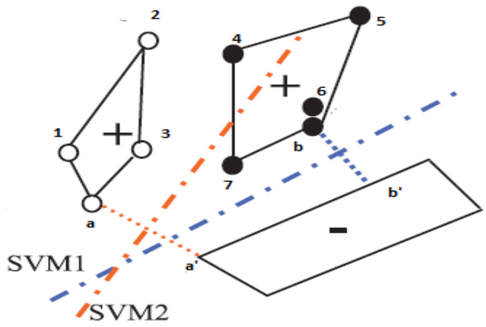

Figure 8: Convex polygon and their SVM

6. Existing System

6.1 Human Detection

The proposed PL-SVM in [21] is contained with two kinds of features for human detection. For this a cascade detector is designed to improve detection performance. A sample of 64 × 128 pixels is divided into cells of size 8 × 8 pixels. Then each group of 2 × 2 cells is integrated into a block in a sliding fashion. The blocks overlap with each other. The gradient orientations of the pixels in the cells are calculated to extract HOG features. Nine dimensional HOG orientations as the features are calculated for each cell. Each block is corresponded by a 36-dimensional feature vector. By dividing each feature bin with the vector module each block is normalized [B6]. Each sample is represented by105 blocks i.e. 420 cells. It corresponding to 3780-dimensional HOG feature vector. In PL-SVM models training is done with the BO features [21] and the HOG features for training samples. As the preprocessing Histogram equalization and median filtering of radius equal to 3 pixels is applied on testing image as preprocessing. An image pyramid is constructed by repeatedly reduced the test image in size by a factor of 1.1. From every layer of the pyramid sliding windows are extracted. For each window BO features are extracted in the first stage and tested with PL-SVM. In the second phase if the window is classified as human then it is tested with PL-SVM with the HOG features.

6.2 PL-SVM Model

A PL-SVM (Piecewise linear support vector machine) [21] is formed from K linear SVMs. It is represented as a piecewise linear function as follows:

$$f(x) = \underset{f_k(x),\ x\in\Omega_k}{\arg\max} \{C_k(x)\} \quad (18)$$

Here, $f_k(x) = w_k^T.x + b_k, k = 1, \ldots \ldots K$, represents the k^{th} local linear SVM. w_k^T represents normal vector. The threshold is represented by b_k. In (18) $\Omega_k = \Omega_k^+ \cup \Omega^-$denotes the k^{th} subspace of the training samples and it is shown in Fig. 9 [21].
In (18), $C_k(x)$ represents the membership degree of a sample x to Ω_k . From the vantage point of probability the membership degree is defined as,

$$C_k(x) = P_k(y = 1|x) \quad (19)$$

Here, P_k (y = 1|x) is the outputted probability of a sample x. The function of the support vector machine is represented by probability as follows:

$$P_k(y = 1|x) = \frac{1.0}{1.0 + \exp(-(A_k \cdot f_k(x) + B_k))} \quad (20)$$

Here A_k and B_k represents the two parameters computed with a maximum likelihood approximation on the training subset [22], and the parameterized sample to hyper plane distance is represented by $A_k \cdot f_k(x) + B_k$.

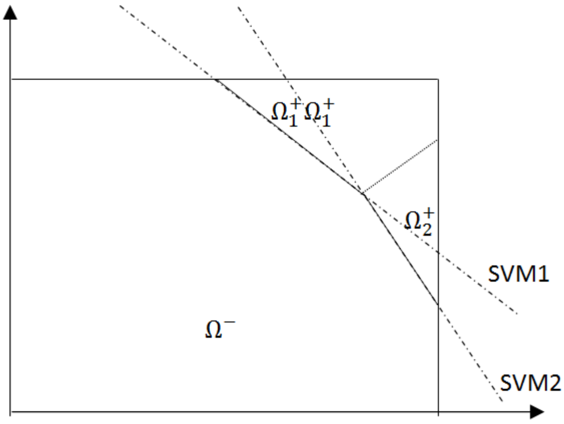

Figure 9: Show the PL-SVM and feature space division. Subspaces are confined with dotted lines and Ω_1^+, Ω_2^+ denote the positive subspaces corresponding to linear SVMs 1, 2, respectively, with Ω^- denoting negatives. Dissimilar positive subspaces are related to samples of different views and postures. Classification boundary of the PL-SVM is noted by bold line segments.

The PL-SVM discriminative function can be converted to a sign function following form for discrimination and detection from (18) while performing classification:

$$F(x) = \text{Sign}\left(f(x)\right) \quad (21)$$

For a given training set $X = \{(x_n, y_n)\}$, $n = 1, . . . , N$, to train the PL-SVM the multi-objective programming problem is needed to be solved:

$$\min\left(\|\omega\|^2 + \lambda \cdot \sum_{n_1}^{\xi_{n_1}}\right), \ldots, \min(\|\omega_k\|^2 + \lambda \cdot \sum_{n_k}^{\xi_{n_k}})$$

$$s.t.\ y_n \cdot F(x_n) - 1.0 + \xi_n \geq 0,\ \ \xi_n \geq 0, n = 1,2, \ldots, N. \quad (22)$$

The above objective function presumes that all of the local SVMs in a PL-SVM are evenly important. Here n_k denotes the sample index in the k^{th} sample subset. Also λ represents the parameter for training error and the SVM margins. ξ represents the slack factor and *F(x)* represents the PL-SVM discriminative function defined in (22).

6.3 PL-SVM Training

The human samples are divided into subsets with a K-mean clustering algorithm in a manifold embedded space before training. When clustering is done to these initial subsets then human samples allotted to the same subset have smaller dissimilarities. This heads to an improved sample division than an arbitrary one.

To build up the human manifolds local linear embedding (LLE) algorithm [17] is employed. The feature space is divided into a number of sub spaces and then piecewise classification is done on each sub-space by SVM. By mapping high-dimensional samples to the low-dimensional space LLE computes the low-dimensional and neighborhood-preserving embedding. When a set of human samples in the high-dimensional feature space is given, LLE begins with detecting nearest neighbors based on the Euclidean distance. LLE discovers the optimal local convex combinations of the nearest neighbors to represent each original sample. Then LLE identifies the optimal local convex combinations of the nearest neighbors to represent each original sample. Then it obtains an embedded space by figuring out a sparse eigenvector problem.

6.4 Training Convergence Analysis

Sequential minimization optimization (SMO) is used for every linear SVMs of the PL-SVM for training and can be following objective function:

$$\min_{\omega_k} \frac{1}{2}\|\omega_k\|^2 + \lambda \cdot \sum_{n_k}^{\xi_{n_k}}$$

$$s.t.\ y_{n_k} \cdot Sign\left(f_k(x_{n_k})\right) - 1.0 + \xi_{n_k} \geq 0,\ \ \xi_{n_k} \geq 0, n_k = 1,2, \ldots, N_k. \quad (23)$$

Here n_k denotes the sample index in the k^{th} subset. Also N_k denotes the number of the samples of the subset. The convergence of the PL-SVM training is analyzed by the nearest point algorithm (NPA) [23]. Let us consider the positive convex hull U_k and the negative convex hull V_k for the k^{th} subset. Also let $\widetilde{u_k} \in U_k$ *and* $\widetilde{v_k} \in V_k$ such that

$$\|\widetilde{u_k} - \widetilde{v_k}\| = \min_{u \in U_k, v \in V_k} \|u - v\| \quad (24)$$

Then the problem of finding $\widetilde{u_k} \in U_k$ *and* $\widetilde{v_k} \in V_k$ is equivalent to finding the solution of k^{th} SVM [23]. According to (19)–(20), the parameterized sample to hyper plane distance of this sample to the hyper plane of this SVM is also the largest. [23] shows that the problem of finding the maximum margin in SVM is same as the problem of finding the nearest point problem (NPP). It shows that SVM problem can be easily transferred to the problem of finding nearest point between two convex polytopes.

7. Conclusion

There are numerous challenges that should be considered through the human detection process. The major problem that faced in human detection is of variation of views and postures. Another difficulty that is faced is to use which feature and classifier for human detection. A study of features and classifier is presented. HOG feature is found out to be most popular features. SVM classifier has also reported as an effective classifier for human detection. PL-SVM shows a promising result in the process of human detection. Detecting human posture with PL-SVM is studied and found out to be promising for detecting human views and posture.

References

[1] Y. Xu, D. Xu, S. Lin, T. X. Han, X. Cao, and X. Li, “Detection of sudden pedestrian crossings for driving

assistance systems," IEEE Trans. Circuits Syst. Video Technol., vol. 42, no. 3, pp. 729–739, Jun. 2008.

[2] N. Dalal and B. Triggs, "Histograms of oriented gradients for human detection," in Proc. IEEE Int. Conf. Comput. Vis. Pattern Recognit., Jun. 2005, pp. 886–893.

[3] R. Xu, B. Zhang, Q. Ye, and J. Jiao, "Cascaded L1-norm minimization learning (CLML) classifier for human detection," in Proc. IEEE Int. Conf. Comput. Vis. Pattern Recognit., Jun. 2010, pp. 89–96.

[4] Q. Zhu, S. Avidan, M. Yeh, and K. Cheng, "Fast human detection using a cascade of histograms of oriented gradients," in Proc. IEEE Int. Conf. Comput. Vis. Pattern Recognit., Jul. 2006, pp. 1491–1498.

[5] X. Wang, T. X. Han, and S. Yan, "An HOG-LBP human detector with partial occlusion handling," in Proc. IEEE Int. Conf. Comput. Vis., Oct. 2009, pp. 32–39.

[6] Q. Ye, J. Jiao, and B. Zhang, "Fast pedestrian detection with multi-scale orientation features and two-stage classifiers," in Proc. IEEE 17th Int. Conf. Image Process., Sep. 2010, pp. 881–884.

[7] W. Gao, H. Ai, and S. Lao, "Adaptive contour features in oriented granular space for human detection and segmentation," in Proc. IEEE Int. Conf. Comput. Vis. Pattern Recognit., Jun. 2009, pp. 1786–1793.

[8] T. Serre, L. Wolf, S. Bileschi, M. Riesenhuber, and T. Poggio, "Object recognition with cortex-like mechanisms," IEEE Trans. Pattern Anal. Mach. Intell., vol. 29, no. 3, pp. 411–426, Mar. 2007.

[9] M. Enzweiler and D. M. Gavrila, "Multilevel mixture-of-experts framework for pedestrian classification," IEEE Trans. Image Process., vol. 20, no. 10, pp. 2967–2979, Oct. 2011.

[10] S. Maji, A. C. Berg, and J. Malik, "Classification using intersection kernel support vector machines is efficient," in Proc. IEEE Int. Conf. Comput. Vis. Pattern Recognit., Jun. 2008, pp. 1–8.

[11] B. Wu and R. Nevatia, "Cluster boosted tree classifier for multi-view, multi-pose object detection," in Proc. IEEE Int. Conf. Comput. Vis., Oct. 2007, pp. 1–8.

[12] S. Z. Li and Z. Zhang, "Floatboost learning and statistical face detection," IEEE Trans. Pattern Anal. Mach. Intell., vol. 26, no. 9, pp. 1112–1123, Sep. 2004.

[13] C. H. Lampert, "An efficient divide-and-conquer cascade for nonlinear object detection," in Proc. IEEE Int. Conf. Comput. Vis. Pattern Recognit., Jun. 2010, pp. 1022–1029.

[14] P. F. Felzenszwalb, R. B. Girshick, D. McAllester, and D. Ramanan,"Object detection with discriminatively trained part based models," IEEE Trans. Pattern Anal. Mach. Intell., vol. 32, no. 9, pp. 1627–1645, Sep. 2010.

[15] P. Ott and M. Everingham, "Shared parts for deformable part-based models," in Proc. IEEE Int. Conf. Comput. Vis. Pattern Recognit., Jun. 2011, pp. 1513–1520.

[16] O. Oladunni and G. Singhal, "Piecewise multi-classification support vector machines," in Proc. Int. Joint Conf. Neural Netw., Jun. 2009, pp. 2323–2330.

[17] S. Q. Ren, D. Yang, X. Li, and Z. W. Zhuang, "Piecewise support vector machines," Chin. J. Comput., vol. 32, no. 1, pp. 77–85, 2009.

[18] H. B. Cheng, P.-N. Tan, and R. Jin, "Efficient algorithm for localized support vector machine," IEEE Trans. Knowl. Data Eng., vol. 22, no. 4, pp. 537–549, Apr. 2010.

[19] Y. Li, B. Liu, X. Yang, Y. Fu, and H. Li, "Multiconlitron: A general piecewise linear classifier," IEEE Trans. Neural Netw., vol. 22, no. 2, pp. 276–289, Feb. 2011.

[20] Y. Lee, Y. Lin, and G. Wahba, "Multicategory support vector machines," Dept. Stat., Univ. Wisconsin-Madison, Madison, Tech. Rep. 1063, 2001.

[21] Qixiang Ye, Zhenjun Han, Jianbin Jiao, Jianzhuang Liu, "Human Detection in Images via Piecewise Linear Support Vector Machines," IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 22, NO. 2, FEBRUARY 2013

[22] J. C. Platt, "Probabilistic outputs for support vector machines and comparisons to regularization likelihood methods," in Proc. Adv. Large Marg. Classifiers, 1999, pp. 61–74.

[23] S. S. Keerthi, S. K. Shevade, C. Bhattacharyya, and K. R. K. Murthy, "Afast iterative nearest point algorithm for support vector machine classifierdesign," IEEE Trans. Neural Netw., vol. 11, no. 1, pp. 124–136, Jan.2000.