Multi-Target Tracking with Sparse Group Features using Discrete-Continuous Optimization

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Abstract. Multi-target tracking of pedestrians is a challenging task due to uncertainty about targets, caused mainly by similarity between pedestrians, occlusion over a relatively long time and a cluttered background. A usual scheme for tackling multi-target tracking is to divide it into two sub-problems: data association and trajectory estimation. A reasonable approach is based on joint optimization of a discrete model for data association and a continuous model for trajectory estimation in a Markov Random Field framework. Nonetheless, usual solutions of the data association problem are based only on location information, while the visual information in the images is ignored. Visual features can be useful for associating detections with true targets more reliably, because the targets usually have discriminative features. In this work, we propose a combination of position and visual feature information in a discrete data association model. Moreover, we propose the use of group Lasso regularization in order to improve the identification of particular pedestrians, given that the discriminative regions are associated with particular visual blocks in the image. We find promising results for our approach in terms of precision and robustness when compared with a state-of-the-art method in standard datasets for multi-target pedestrian tracking.

1 Derivation of gradient and Hessian of unregularized energy function

In our method, we must minimize the unregularized version of energy function given by Equation **3**, this problem is given by:

$$w_l^* = \arg\min_{w_l} E_{PL:d}^{T(u)}(w_l) = \arg\min_{w_l} \sum_{d \in D} \left\{ K_d + c_j^t \alpha \, log(1 + exp(-y_l^d w_l^T x_t^j)) \right\} \quad (1)$$

By calling the gradient $\nabla_{w_l} E_{PL:d}^{T(u)}(w_l)$ as $G(w_l)$, this term is calculated as following:

$$G(w_l) = \frac{\partial}{\partial w_l} \sum_{d \in D} \Big\{ K_d + c_j^t(\alpha \, log(1 + exp(-y_l^d(w_l^T x_t^j)))) - ln(Z_{loc}^d) \Big\}$$

$$G(w_l) = \sum_{d \in D} \left\{ c_j^t \alpha \frac{\partial}{\partial w_l} log(1 + exp(-y_l^d(w_l^T x_t^j))) - \frac{\partial}{\partial w_l} ln(Z_{loc}^d) \right\}$$

$$G(w_l) = \sum_{d \in D} \left\{ c_j^t \alpha \frac{\frac{\partial}{\partial w_l}\left[1 + exp(-y_l^d(w_l^T x_t^j))\right]}{1 + exp(-y_l^d(w_l^T x_t^j))} - \frac{\frac{\partial}{\partial w_l}\left[Z_{loc}^d\right]}{Z_{loc}^d} \right\}$$

$$G(w_l) = \sum_{d \in D} \left\{ c_j^t \alpha \frac{exp(-y_l^d(w_l^T x_t^j)) - y_l^d(x_t^j)}{1 + exp(-y_l^d(w_l^T x_t^j))} \right.$$
$$\left. - \frac{\sum_m exp\left(E_{PL:d}^{T(u)}(w_l, y_m)\right) \frac{\partial}{\partial w_l}\left[c_j^t \alpha log(1 + exp(-y_m^d(w_l^T x_t^j)))\right]}{Z_{loc}^d} \right\}$$

$$G(w_l) = \sum_{d \in D} \left\{ c_j^t \alpha \frac{exp(-y_l^d(w_l^T x_t^j)) - y_l^d(x_t^j)}{1 + exp(-y_l^d(w_l^T x_t^j))} \right.$$
$$\left. - \sum_m \frac{exp\left(E_{PL:d}^{T(u)}(w_l, y_m)\right)}{Z_{loc}^d} \left[c_j^t \alpha \frac{exp(-y_m^d(w_l^T x_t^j))}{1 + exp(-y_m^d(w_l^T x_t^j))} - y_m^d(x_t^j) \right] \right\}$$

$$G(w_l) = -\alpha \sum_{d \in D} \left\{ c_j^t \left[p_d(\bar{y}_l/d; w_l) y_l^d(x_t^j) \right] - \sum_m c_j^t \, p_m(y_m/d; w_l) \left[p_d(\bar{y}_m/d; w_l) y_m^d(x_t^j) \right] \right\}$$

$$G(w_l) = -\alpha \sum_{d \in D} \left\{ c_j^t \left[p_d(\bar{y}_l/d; w_l) y_l^d(x_t^j) - \left\langle p_d(\bar{y}_m/d; w_l) y_m^d(x_t^j) \right\rangle_{p_m(y_m/d; w_l)} \right] \right\} \qquad (2)$$

We call the Hessian $H_{w_l}(E_{PL:d}^{T(u)}(w_l))$ as $H(w_l)$ and calculate it from gradient expression as following:

$$H(w_l) = -\alpha \frac{\partial}{\partial w_l^T} \sum_{d \in D} \left\{ c_j^t \left[p_d(y_l/d; w_l) y_l^d(x_t^j) - \left\langle p_d(y_m/d; w_l) y_m^d(x_t^j) \right\rangle_{p_m(y_m/d; w_l)} \right] \right\}$$

$$H(w_l) = -\alpha \sum_{d \in D} \left\{ c_j^t x_t^j {x_t^j}^T \left[p_d(y_l/d; w_l)(1 - p_d(y_l/d; w_l)) \right. \right.$$
$$\left. \left. - \left\langle (1 - p_d(y_l/d; w_l)) p_d(y_m/d; w_l) \right\rangle_{p_m(y_m/d; w_l)} \right] \right\} \qquad (3)$$

With both terms, we can optimize the Equation 1 with Newton's method in order to estimate the optimal value of weight vector w.