# Fast Temporal Activity Proposals for Efficient Detection of Human Actions in Untrimmed Videos (Supplementary Material)

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# Abstract

In this supplementary material, we complement our paper submission by providing additional analysis of the optimization problems (Section 1) and qualitative results (Section 2).

# 1. Optimization details

In this section, we elaborate on the details required to solve the optimization problems proposed in our paper, specifically, the Class-Independent Proposal Learning and Class-Induced Proposal Learning problems. These details will help reproduce the results we achieve in the experimental section. For completeness, we reiterate both problems in Eqs (1) and (2).

$$(\mathbf{D}_U, \mathbf{A}^*) = \underset{\mathbf{D}, \mathbf{A}}{\operatorname{arg\,min}} \frac{1}{n} \|\mathbf{X} - \mathbf{D}\mathbf{A}\|_F^2 + \lambda \|\mathbf{A}\|_{2,1}$$
(1)

$$(\mathbf{D}_S, \mathbf{A}^*, \mathbf{W}^*) = \underset{\mathbf{D}, \mathbf{A}, \mathbf{W}}{\operatorname{arg\,min}} \frac{1}{n} \|\mathbf{X} - \mathbf{D}\mathbf{A}\|_F^2 + \lambda_1 \|\mathbf{A}\|_{2,1} + \lambda_2 \|\mathbf{W}^T \mathbf{A} - \mathbf{Y}\|_F^2 + \lambda_3 \|\mathbf{W}\|_F^2,$$
(2)

# **1.1. Solving Eq (1) Using Alternating Optimization**

To solve Eq (1), we follow a conventional strategy of fixed point optimization, which iteratively updates each of the variables  $D_U$  and A separately by fixing one of them at a time.

#### 1.1.1 Fix D and update A (Step 1)

It requires the solution of Eq (3):

$$\mathbf{A}^{k+1} = \underset{\mathbf{A}}{\operatorname{arg\,min}} \frac{1}{n} \|\mathbf{X} - \mathbf{D}\mathbf{A}\|_{F}^{2} + \lambda \|\mathbf{A}\|_{2,1}$$
(3)

The problem in Eq (3) is a classical extension of the Lasso problem with  $L_{2,1}$  matrix norm. We can solve it efficiently using ADMM by introducing a slack variable **Z**, which separates the two terms in the optimization.

$$\underset{\mathbf{A},\mathbf{Z}}{\operatorname{arg\,min}} \frac{1}{n} \|\mathbf{X} - \mathbf{D}\mathbf{A}\|_{F}^{2} + \lambda \|\mathbf{Z}\|_{2,1}$$
  
subject to  $\mathbf{A} = \mathbf{Z}$  (4)

The augmented Lagrangian is:

$$\mathbf{L} = \frac{1}{n} \|\mathbf{X} - \mathbf{D}\mathbf{A}\|_{F}^{2} + \lambda \|\mathbf{Z}\|_{2,1} + \operatorname{Tr}(\mathbf{\Lambda}^{T}(\mathbf{A} - \mathbf{Z})) + \frac{\rho}{2} \|\mathbf{A} - \mathbf{Z}\|_{F}^{2}$$
(5)

Solving the above problem requires an iterative process, where (A, Z) are updated separately by minimizing the augmented Lagrangian function while  $\Lambda$  is updated by performing gradient ascent on the dual problem.

Update A:

$$\underset{\mathbf{A}}{\operatorname{arg\,min}} \frac{1}{n} \|\mathbf{X} - \mathbf{D}\mathbf{A}\|_{F}^{2} + \operatorname{Tr}(\mathbf{\Lambda}^{T}\mathbf{A}) + \frac{\rho}{2} \|\mathbf{A} - \mathbf{Z}\|_{F}^{2}$$
(6)

This is a strongly convex problem that is solved by setting the gradient to 0. To do this, we need to solve the following linear system:

$$(\mathbf{D}^T \mathbf{D} + \rho \mathbf{I})\mathbf{A} = \mathbf{D}^T \mathbf{X} - \mathbf{\Lambda} + \rho \mathbf{Z}$$
(7)

If  $(\mathbf{D}^T \mathbf{D} + \rho \mathbf{I})^{-1}$  can be efficiently computed offline, we can solve this subproblem as:

$$\mathbf{A} = (\mathbf{D}^T \mathbf{D} + \rho \mathbf{I})^{-1} (\mathbf{D}^T \mathbf{X} - \mathbf{\Lambda} + \rho \mathbf{Z})$$
(8)

Update Z:

$$\underset{\mathbf{Z}}{\operatorname{arg\,min}} \frac{\rho}{2} \|\mathbf{A} - \mathbf{Z}\|_{F}^{2} - \operatorname{Tr}(\mathbf{\Lambda}^{T}\mathbf{Z}) + \lambda \|\mathbf{Z}\|_{2,1}$$
(9)

$$\underset{\mathbf{Z}}{\operatorname{arg\,min}} \frac{1}{2} \|\mathbf{A} - \mathbf{Z}\|_{F}^{2} - \frac{1}{\rho} \operatorname{Tr}(\mathbf{\Lambda}^{T} \mathbf{Z}) + \frac{\lambda}{\rho} \|\mathbf{Z}\|_{2,1}$$
(10)

$$\underset{\mathbf{Z}}{\operatorname{arg\,min}} \frac{1}{2} \|\mathbf{Z} - (\mathbf{A} + \frac{\mathbf{\Lambda}}{\rho})\|_{F}^{2} + \frac{\lambda}{\rho} \|\mathbf{Z}\|_{2,1}$$
(11)

$$\underset{\{\hat{\mathbf{z}}_{i}\}_{i=1}^{d}}{\operatorname{arg\,min}} \sum_{i=1}^{d} (\frac{1}{2} \| \hat{\mathbf{z}}_{i} - (\hat{\mathbf{A}}_{i} + \frac{\hat{\mathbf{\Lambda}}_{i}}{\rho})) \|_{2}^{2} + \frac{\lambda}{\rho} \| \hat{\mathbf{z}}_{i} \|_{2}$$
(12)

where d is the number of rows of A and  $\hat{z}_i$  denotes the  $i^{th}$  row of Z. We can solve for each row of Z independently using the identity:

$$\arg\min_{\hat{\mathbf{z}}_{i}} \sum_{i=1}^{d} \left(\frac{1}{2} \| \hat{\mathbf{z}}_{i} - (\hat{\mathbf{A}}_{i} + \frac{\hat{\mathbf{\Lambda}}_{i}}{\rho}) \right) \|_{2}^{2} + \frac{\lambda}{\rho} \| \hat{\mathbf{z}}_{i} \|_{2}$$
$$= \max(0, 1 - \frac{\lambda}{\rho \| \hat{\mathbf{A}}_{i} + \frac{\hat{\mathbf{\Lambda}}_{i}}{\rho} \|_{2}}) (\hat{\mathbf{A}}_{i} + \frac{\hat{\mathbf{\Lambda}}_{i}}{\rho})$$
(13)

Update Λ:

$$\mathbf{\Lambda} \Leftarrow \mathbf{\Lambda} + \rho(\mathbf{A} - \mathbf{Z}) \tag{14}$$

#### 1.1.2 Fix A and update D (Step2)

This update requires the solution to Eq (15), which is a linear least squares problem in matrix form.

$$\mathbf{D^{k+1}} = \underset{\mathbf{D}}{\operatorname{arg\,min}} \frac{1}{n} \|\mathbf{X} - \mathbf{DA}\|_{F}^{2}$$
$$\mathbf{D^{k+1}} = \underset{\mathbf{D}}{\operatorname{arg\,min}} \|\mathbf{X}^{T} - \mathbf{A}^{T}\mathbf{D}^{T}\|_{F}^{2}$$
(15)

We can solve the problem using Eq (16):

$$\mathbf{D}^{\mathbf{k}+1} = ((\mathbf{A}\mathbf{A}^T)^{-1}\mathbf{A}\mathbf{X}^T)^T = \mathbf{x}\mathbf{A}^T(\mathbf{A}\mathbf{A}^T)^{-1}$$
(16)

Notice that we initialize **D** using K-Means.

#### 1.2. Solving Eq (2) Using Alternating Optimization

We solve this problem using alternating optimization.

# 1.2.1 Fix D and update A (Step 1)

In this step, we solve the problem in Eq (17)

$$\mathbf{A}^{k+1} = \underset{\mathbf{A}}{\operatorname{arg\,min}} \frac{1}{n} \|\mathbf{X} - \mathbf{D}\mathbf{A}\|_{F}^{2} + \lambda_{1} \|\mathbf{A}\|_{2,1} + \lambda_{2} \|\mathbf{W}^{T}\mathbf{A} - \mathbf{Y}\|_{F}^{2}$$
$$\mathbf{A}^{k+1} = \underset{\mathbf{A}}{\operatorname{arg\,min}} \|\mathbf{U} - \mathbf{V}\mathbf{A}\|_{F}^{2} + \lambda_{1} \|\mathbf{A}\|_{F}^{2}$$
(17)

where,  $\mathbf{U} = \begin{bmatrix} \frac{1}{\sqrt{n}} \mathbf{X}^T \sqrt{\lambda_2} \mathbf{Y}^T \end{bmatrix}^T$  and  $\mathbf{V} = \begin{bmatrix} \frac{1}{\sqrt{n}} \mathbf{D} \sqrt{\lambda_2} \mathbf{W}^T \end{bmatrix}^T$ . Note that problem in Eq (17) can be solved in the same way we solve Eq (3).

# 1.2.2 Fix all variables except D (Step 2)

Notice that we get the same optimization problem described in Eq (15).

### **1.2.3** Fix all the variables except W (step 3)

We get a least squares problem in matrix form:

$$\mathbf{W}^{k+1} = \underset{\mathbf{W}}{\operatorname{arg\,min}} \lambda_2 \|\mathbf{W}^T \mathbf{A} - \mathbf{Y}\|_F^2 + \lambda_3 \|\mathbf{W}\|_F^2$$
(18)

$$\mathbf{W}^{k+1} = \underset{\mathbf{W}}{\operatorname{arg\,min}} \|\mathbf{A}^{T}\mathbf{W} - \mathbf{Y}^{T}\|_{F}^{2} + \frac{\lambda_{3}}{\lambda_{2}} \|\mathbf{W}\|_{F}^{2}$$
(19)

Eq (19) can be solved by handling the following linear system:

$$2(\mathbf{A}\mathbf{A}^{T})\mathbf{W} - 2\mathbf{A}\mathbf{Y}^{T} + \frac{2\lambda_{3}}{\lambda_{2}}\mathbf{W} = 0$$
$$(\mathbf{A}\mathbf{A}^{T} + \frac{\lambda_{3}}{\lambda_{2}}\mathbf{I})\mathbf{W} = \mathbf{A}\mathbf{Y}^{T}$$
$$\mathbf{W}^{k+1} = (\mathbf{A}\mathbf{A}^{T} + \frac{\lambda_{3}}{\lambda_{2}}\mathbf{I})^{-1}\mathbf{A}\mathbf{Y}^{T}$$
(20)

# 2. Complementary Qualitative Results

Here, we provide complementary qualitative results of the proposal segments generated by our method. In Figure 1, we show the top-5 best ranked proposal segments from the entire Thumos14 testing set. We observe that the most confident predictions produced by our method are strongly correlated with a known action category.



Figure 1. Top-5 best ranked proposals from entire Thumos14 testing set.



Figure 2. Bottom-5 worst ranked proposals from entire Thumos14 testing set.

We also investigate the bottom-5 worst ranked proposals in Figure 2. Our proposal method is able to discard (or assign a low score) the proposal candidates that are not related with human actions. Interestingly, we also discard the candidate proposals that contains unknown actions. For example, the third row in Figure 2 shows a proposal that confines a penalty kick foul action which it is not annotated in Thumos14.

Finally, we add additional examples of retrieved proposals in Figure 3. We provide a live example of these proposals in the following link: http://www.cabaf.net/temporalproposals/demo.



Figure 3. Additional examples of retrieved proposals. Watch the proposal segments in the following link: http://www.cabaf.net/temporalproposals/demo.