Multi-task learning for jersey number recognition in Ice Hockey

Kanav Vats, Mehrnaz Fani, David A. Clausi and John Zelek
{k2vats,mfani,dclausi,jzelek}@uwaterloo.ca
University of Waterloo
Waterloo, Ontario, Canada

ABSTRACT

Identifying players in sports videos by recognizing their jersey numbers is a challenging task in computer vision. We have designed and implemented a multi-task learning network for jersey number recognition. In order to train a network to recognize jersey numbers, two output label representations are used (1) Holistic - considers the entire jersey number as one class, and (2) Digit-wise - considers the two digits in a jersey number as two separate classes. The proposed network learns both holistic and digit-wise representations through a multi-task loss function. We determine the optimal weights to be assigned to holistic and digit-wise losses through an ablation study. Experimental results demonstrate that the proposed multi-task learning network performs better than the constituent holistic and digit-wise single-task learning networks.

CCS CONCEPTS
• Computing methodologies → Artificial intelligence; Computer vision; Computer vision problems; Object recognition;

KEYWORDS
CNN, multi-task, jersey number, sport analytics

1 INTRODUCTION

Automated player identification in team sports using broadcast game video is a challenging task. Although there are approaches for some sports (e.g., basketball [12]) that identify players using body appearances, this is not achievable in ice hockey due to the players wearing bulky equipment and helmets that occlude body characteristics and skin color, especially reducing the discriminability between players on the same team that wear the same color uniforms and helmets. For ice hockey, this leaves jersey numbers as the primary method of performing player identification from game video. Although approaches for digit recognition exist [3], high motion blur, occlusions, and single camera views make this a challenging automation problem for ice hockey.

In the literature, there exist several deep learning approaches for jersey number recognition [1, 2, 7, 8]. These approaches consider jersey number recognition as a classification problem and either (1) consider the jersey numbers as separate classes [1, 2], or (2) treat the two digits in a jersey number as two independent classes [7, 8]. Since learning multiple output representations through multi-task learning can lead to improved regularization [10], we hypothesize that learning both of these representation together in a multi-task loss can result in better performance.

In this paper, we utilize multi-task learning for simultaneously learning the digit-wise and holistic jersey number representations for improving network generalization. Two contributions are recognized:

(1) We design a loss function consisting of the combination of (1) “Holistic” representation loss term treating the jersey number as a separate class (2) “Digit-wise” representation loss term treating digits in a number as independent classes.

(2) Due to lack of publicly available datasets for jersey number recognition, we also introduce a jersey number dataset consisting of more than 50,000 images for the game of ice hockey.

We conduct an ablation study to demonstrate that the holistic and digit-wise losses complement each other with appropriate weight given to them. Experimental results demonstrate that the proposed multi-task loss performs better than using only the holistic loss or the digit-wise loss.

2 BACKGROUND

Traditionally, jersey number recognition was performed with the help of hand-crafted features [13, 14]. Gerke et al. [2] were the first to use deep networks (CNN) for jersey number recognition with small low resolution images. The CNN outperformed hand crafted HOG features by a huge margin. Li et al. [7] use a spatial transformer network (STN) to better localize jersey numbers and use human labeled quadrangle, annotating the jersey number area, to train the network with semi-supervised learning. Liu et al. [8] treat the problem as a jersey number detection and recognition problem using a Faster RCNN [9] inspired network incorporating human pose keypoint supervision. Gerke et al. [1] complement vision based jersey number recognition model with player location based features based on the assumption that players do not move randomly on the field, but follow a tactical role such as defender, winger or forward.

In the literature, multi-task learning has been utilized for digit and text recognition. How et al. [5] use a multi-task learning network to simultaneously learn handwritten numeral recognition and determine whether the digit is scratchy. Kim et al. [6] use multi-task...
Figure 1: The input image is passed through a Resnet 34 network after which the 512 dimensional features are extracted from the pre-final layer. \( p_i, i \in \{1, 2\} \) and \( p \) are 11 and 81-dimensional vectors representing the digit probabilities and holistic number probabilities respectively. \( L_1 \) and \( L_2 \) denotes the individual first and second digit loss respectively and \( L \) denotes the holistic loss.

3 METHODOLOGY

3.1 Dataset

Datasets used in recent works [1, 2, 7, 8] are not publicly available, hence we created our own dataset. The dataset consists of 34,251 player bounding boxes obtained from 25 National Hockey League (NHL) games. The NHL game videos are of resolution \( 1280 \times 720 \) pixels. The dataset contains a total of 81 jersey number classes, including an additional null class for no jersey number visible. The dataset is much bigger than the datasets used in other works such as Gerke et al. [2] with 8,281 images and Liu et al. [8] with 3,567 images. Although the dataset used in Li et al. [7] has 215,036 images, 90% of the images are negative samples (no jersey number present). Hence, our dataset has more images with a non-null jersey number than Li et al. [7].

The player head and bottom of the images are cropped such that only the jersey number is visible. Fig. 2 shows some example images from the dataset. A number was considered readable when both constituent digits were visible, however, images with partial occlusion due to motion blur and jersey kinks were included in the dataset since those situations are very common and a model working in sports scenarios should handle those situations. A digit was considered unreadable when either one/both of its constituent digits was fully occluded/invisible. Two annotators annotated the entire dataset.

Images from 17 games are used for training, four games for validation and four games for testing. The exact number of images in the splits is shown in Table 1. The splits are constructed at a game level, so that there is no inherent in-game bias present during validation or testing. The dataset is highly imbalanced such that the ratio between the most frequent and least frequent class is 92. The class distribution in the dataset is illustrated in Fig. 4. The dataset covers a range of real-game scenarios such as occlusions, motion blur and self occlusions. We plan on making the dataset publicly available in future.

Table 1: Number of images in train, validation and test set

|       | Train | Validation | Test  |
|-------|-------|------------|-------|
| Images| 33,436| 6,770      | 9,025 |

3.2 Network Design

To solve the previously described problem, i.e., players’ jersey number recognition in broadcast ice hockey videos, a network with a multi-task loss, as shown in Fig. 1, is designed and implemented. The input image of dimension \( 300 \times 300 \) pixels is passed through a Resnet34 [4] network to obtained 512-dimensional features from the pre-final layer. The features are then passed through three linear layers followed by softmax layers to output three probabilities. The first linear layer outputs an 81-dimensional vector \( p \in \mathbb{R}^{81} \) representing the probability distribution over the 81 jersey number classes. The second and third linear layers output an 11-dimensional vectors \( p_1, p_2 \in \mathbb{R}^{11} \) representing the probability of the first and second digit respectively. The one additional class in the 11-dimensional vector denotes the absence of a jersey number. Let \( y \in \mathbb{R}^{81}, y_1 \in \mathbb{R}^{11} \) and \( y_2 \in \mathbb{R}^{11} \) denote the ground truth vectors corresponding to the jersey number, first digit and second digit respectively.

The multi-task loss consists of three components:

1. The holistic loss \( L \).

\[
L = - \sum_{j=1}^{81} y_j \log p^j
\]  

2. The first digit loss \( L_1 \).

\[
L_1 = - \sum_{j=1}^{11} y_{1j} \log p_{1j}
\]  

3. The second digit loss \( L_2 \).

\[
L_2 = - \sum_{k=1}^{11} y_{2k} \log p_{2k}
\]
Figure 2: Examples of images from the dataset. The dataset cover many real-game scenarios such as (a) occlusions from external objects, (b)(c) motion blur, and (d) self-occlusion.

Figure 3: Validation accuracy vs number of iterations for the multi-task learning (MTL), holistic and digit-wise loss settings. The multi-task setting shows the best performance among the three settings.

Each of the three losses is a cross-entropy loss between the ground truth and the predicted distribution. The overall loss $L_{tot}$ is given by

$$L_{tot} = \alpha \cdot L + \beta \cdot L_1 + \gamma \cdot L_2$$

where $\alpha, \beta, \gamma$ denote weights given to each loss such that $\alpha+\beta+\gamma = 1$. Also,

$$\beta \cdot L_1 + \gamma \cdot L_2$$

is the overall digit-wise loss and $\beta + \gamma$ is the total weight given to the digit-wise loss.

3.3 Training details

For data augmentation, we perform color jittering with high values of the $hue$ parameter. Affine transformations are however not performed since they lead to a decrease in performance. This is because transformations such as scaling can often make a jersey number not visible since each image has a different scale. The training is done for 10,000 iterations with Adam optimizer initial learning rate of .001 and $L2$ weight decay of .001. The learning rate is decreased by a factor of 0.33 after 2000, 4000, 6000 and 7000 iterations. A batch size 100 is used on a single 1080Ti GPU.

4 RESULTS AND DISCUSSION

We compare the proposed multi-task loss with holistic and digit-wise losses by simply removing the other loss branch from the network. For the digit-wise setting, a predicted number is classified correctly when both of its digits are classified correctly. From Table 5, the multi-task loss gives an accuracy of 89.6% and a macro averaged F1 score of 91.2% and outperforms the holistic (accuracy 87.6%) and digit-wise losses (accuracy 88.1%). Fig. 3 shows the validation accuracy for the three settings during 10,000 training iterations. The multi-task loss outperforms holistic and digit-wise losses during training.

We implemented Gerke et al. [2] model on our dataset and found the performance low (45.7% test accuracy). We believe that the reasons for this low performance are (1) The much bigger size of our dataset compared to Gerke et al. [2] that lowered the generalizability Gerke et al. (2) Ice hockey is a more challenging domain for jersey number recognition.
Table 2: Comparison of accuracy values with different values of loss weight coefficients for the multi-task setting

| α  | β  | γ  | Test Acc | Precision | Recall | F1 score |
|----|----|----|----------|-----------|--------|----------|
| 1  | 0  | 0  | 87.6     | 90.9      | 87.7   | 88.7     |
| 0.5| 0.25| 0.25| 89.1     | 92.3      | 89.1   | 90.2     |
| 0.33| 0.33| 0.33| 88.4     | 92.7      | 88.4   | 90.0     |
| 0.3| 0.35| 0.35| 89.6     | 93.6      | 89.6   | 91.2     |
| 0.2| 0.4| 0.4| 89.6     | 92.8      | 89.6   | 90.9     |
| 0.1| 0.45| 0.45| 89.0     | 92.9      | 89.07  | 90.6     |
| 0 | 0.5| 0.5| 88.1     | 92.5      | 88.1   | 89.9     |

Figure 5: Some common sources of error are (a) occlusions from external sources, (b) folding of jersey, (c) faulty bounding boxes, and (d) camera viewpoints not covering the whole jersey.

Table 3: Comparison of datasets in literature

| Dataset | Number of images |
|---------|------------------|
| Gerke et al. [2] | 8,281 |
| Liu et al. [8]  | 3,567 |
| Ours  | 54,251 |

Table 4: Comparison of accuracy values with different backbone networks

| Backbone | Test Acc | Precision | Recall | F1 score |
|----------|----------|-----------|--------|----------|
| Mobilenetv2 | 87.9     | 91.8      | 87.9   | 89.3     |
| Resnet18 | 89.1     | 92.5      | 89.1   | 90.3     |
| Resnet34 | 89.6     | 93.6      | 89.6   | 91.2     |

number identification than soccer due to high motion blur from fast moving-camera.

We also implemented the version of Li et al. [7] on our dataset without using spatial transformer localization loss since it requires ‘quadrangle’ annotations as mentioned in Li et al. [7]. The accuracy obtained was 80.0% with F1 score of 82.5% (Table 5). We further replaced the classification cross entropy loss function in Li et al. [7] with the proposed loss function and found an improvement in accuracy of 1.6% (81.6% accuracy) and F1 score of 1.2% (83.7% F1 score) demonstrating the effectiveness of the proposed loss function. We could not compare our model with Liu et al. [8] since training Liu et al. [8] model requires digit level bounding boxes and human keypoint annotations which our dataset does not have and there are no trained models provided by the authors to be used publicly for testing.

Fig. 5 shows some interesting failure cases. Partial occlusions are common and can result in misinterpretation of jersey numbers (Fig. 5 part a). Other sources of failures are folding of jersey leading to errors Fig. 5 part b, jersey numbers not fully present in player bounding boxes (Fig. 5 part c) and jersey number occluded due to camera viewpoints (Fig. 5 part d).

4.1 Ablation study

We perform an ablation study on the loss weights α, β, and γ to determine how the digit-wise and holistic losses affect accuracy. The analysis can be seen in Table 2. We observe that giving a higher weight to the digit-wise loss (β + γ = 0.7) gives the highest accuracy (89.6%) and F1 score (91.2%). However, having a high value of holistic loss weight (α = 0.8) results in a lower accuracy (87.8%) and F1 score (89.0%). This makes sense because on its own, the digit-wise loss gives better accuracy compared to holistic loss (Table 5). However, as β + γ is further increased to 0.9 the accuracy decreases (89%). This demonstrates that holistic and digit-wise losses complement each other when an appropriate weight is given to both losses. The accuracy is maximized when the digit-wise loss is given slightly more than double the weight of the holistic loss. The best values are α = 0.3, β = 0.35 and γ = 0.35.

We also do an ablation study on the backbone network used in the experiment in Table 4. Two additional backbones were tested: Resnet18 [4], Mobilenetv2 [11], while keeping other parameters including the loss weights α, β, γ fixed to their optimal values of 0.3, 0.35, 0.35. Resnet 34 showed the best performance followed by
Resnet18 and MobileNetv2. We did not test bigger networks such as Resnet 50 since it could not fit a batch size of 100 on a single GPU.

5 CONCLUSION

In this paper, we introduce a simple multi-task learning network for player’s jersey number recognition in ice hockey broadcast video frames. We also create a new dataset with more than 50,000 images to test the network. The network learns both the holistic and digit-wise representations of jersey number labels which resulted in improved regularization and accuracy. The methodology is however, task agnostic and can be used in other number recognition tasks.

6 ACKNOWLEDGEMENT

This work was supported by Statathletes through the Mitacs Accelerate Program and Natural Sciences and Engineering Research Council of Canada (NSERC).

REFERENCES

[1] Sebastian Gerke, Antje Linnemann, and Karsten Müller. 2017. Soccer player recognition using spatial constellation features and jersey number recognition. Computer Vision and Image Understanding 159 (2017), 105 – 115. https://doi.org/10.1016/j.cviu.2017.04.010

[2] S. Gerke, K. Müller, and R. Schafer. 2015. Soccer Jersey Number Recognition Using Convolutional Neural Networks. In 2015 IEEE International Conference on Computer Vision Workshop (ICCVW). 734–741. https://doi.org/10.1109/ICCVW.2015.100

[3] Ian Goodfellow, Yoshua Bengio, Aaron Courville. 2016. Deep Learning. MIT Press, Cambridge, MA, 793 p. https://www.deeplearningbook.org

[4] K. He, X. Zhang, S. Ren, and J. Sun. 2016. Deep Residual Learning for Image Recognition. In 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). 770–778. https://doi.org/10.1109/CVPR.2016.90

[5] J. Hou, H. Zeng, L. Cai, J. Zhu, J. Cao, and J. Hou. 2017. Handwritten numeral recognition using multi-task learning. In 2017 International Symposium on Intelligent Signal Processing and Communication Systems (ISPACS). 155–158. https://doi.org/10.1109/ISPACS.2017.8266444

[6] Hong-Hyun Kim, Je-Kang Park, Joo-Hee Oh, and Dong Kang. 2017. Multi-task convolutional neural network system for license plate recognition. International Journal of Control, Automation and Systems 15 (12 2017), 2942–2949. https://doi.org/10.1007/s12555-016-0332-x

[7] G. Li, S. Xu, X. Liu, L. Li, and C. Wang. 2018. Jersey Number Recognition with Semi-Supervised Spatial Transformer Network. In 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW). 1864–18647. https://doi.org/10.1109/CVPRW.2018.00231

[8] H. Liu and B. Bhanu. 2019. Pose-Guided R-CNN for Jersey Number Recognition in Sports. In 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW). 2457–2466. https://doi.org/10.1109/CVPRW.2019.00301

[9] Shaqing Ren, Kaiming He, Ross Girshick, and Jian Sun. 2015. Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks. In Proceedings of the 28th International Conference on Neural Information Processing Systems - Volume 2 (Montreal, Canada) (NIPS’15). MIT Press, Cambridge, MA, USA, 91–99.

[10] Sebastian Ruder. 2017. An Overview of Multi-Task Learning in Deep Neural Networks. CoRR abs/1706.05098 (2017). arXiv:1706.05098 http://arxiv.org/abs/1706.05098

[11] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L. Chen. 2018. MobileNetV2: Inverted Residuals and Linear Bottlenecks. In 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition. 4510–4520. https://doi.org/10.1109/CVPR.2018.00474

[12] Arda Sencak, Tae-Hyun Oh, Junskim Kim, and In So Kweon. 2018. Part-Based Player Identification Using Deep Convolutional Representation and Multi-Scale Focusing. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR) Workshops.

[13] Qixiang Ye, Shuqiang Jiang, Yang Liu, and Wen Gao. 2005. Jersey number detection in sports video for athlete identification. Proc SPIE 5960 (07 2005), 1599–1606. https://doi.org/10.1117/12.632735

[14] Matko Saric, Hrvoje Dujmic, Vladan Papic, and Nikola Rosic. 2008. Player Number Localization and Recognition in Soccer Video using HSV Color Space and Internal Contours. International Journal of Electrical and Computer Engineering 2, 7 (2008), 1408 – 1412. https://publications.waset.org/vol/19

Table 5: Comparison of accuracy values with holistic, digit-wise and multi-task settings

| Method      | Test Acc | Precision | Recall | F1_score |
|-------------|----------|-----------|--------|----------|
| Holistic    | 87.6     | 90.9      | 87.7   | 88.7     |
| digit-wise  | 88.1     | 92.5      | 88.1   | 89.9     |
| multi-task  | 89.6     | 93.6      | 89.6   | 91.2     |
| Li et al. [7] | 80.0  | 87.1      | 80.0   | 82.5     |
| Li et al. [7] (proposed loss) | 81.6 | 87.9 | 81.6 | 83.7 |
| Gerke et al. [2] | 45.7 | 58.5 | 45.7 | 48.2 |