Abstract

A human action can be seen as transitions between one’s body poses over time, where the transition depicts a temporal relation between two poses. Recognizing actions thus involves learning a classifier sensitive to these pose transitions from given high-dimensional frame representations. In this paper, we introduce transition forests, an ensemble of decision trees that learn transitions between pairs of two independent frames in a discriminative fashion. During training, node splitting is driven by alternating two different criteria: the standard classification entropy that maximizes the discrimination power in individual frames, and the proposed one in pairwise frame transitions. Growing the trees tends to group frames that have similar associated transitions and share same action label. Unlike conventional classification trees where node-wise the best split is determined, the transition forests try to find the best split of nodes jointly (within a layer) for incorporating distant node transitions. When inferring the class label of a new video, frames are independently passed down the trees (thus highly efficient) then a prediction for a certain time-frame is made based on the transitions between previous observed frames and the current one in an efficient manner. We apply our method on varied action recognition datasets showing its suitability over several baselines and state-of-the-art approaches.

1 Introduction

Human action recognition is an important area in computer vision with a wide range of applications e.g. surveillance, robotics, game control, etc. Over the past decades, a significant amount of efforts have been put using RGB videos [1]. With recently introduced cost-effective depth sensors and reliable real-time human body pose estimation [16], human skeleton based action recognition has become an emerging topic.

Recognizing actions from skeleton data is generally regarded as a time series problem where the main challenge is to capture the temporal dynamics of observed frames. Popular approaches to this problem include modelling the whole sequence using generative models such as state-space models [9,12] and deep architectures [4,18]; or tackling it as a classification problem of either the whole sequence [19,20,27] or a small chunk of frames [5,25,26]. Among different classifiers, we consider decision forests, which have been particularly popular in computer vision problems, owing to many desired properties: clusters obtained in leaf nodes, scalability to large datasets, efficiency in prediction, and multi-class learning.

The main limitation of decision forests for temporal problems lies on the assumptions made while encoding the temporal dynamics in the feature space. The whole sequence [24,27] is often represented as a bag-of-features that generally loses temporal structure information. Alternatively, using short sequences of stacked frames [5] requires a more complex feature space while it still does not capture dynamics between chunks of frames. Recently, [3] groups pairs of distant frames to capture the
temporal evolution at the cost of augmenting features and ensemble size. On the other hand, [9] sacrifices the discriminative power of decision forests in favor of a generative tree-structured state-space model (not fully exploiting the benefit of labelled data). How to relieve these limitations of forests has not been deeply studied for action recognition, although we find related attempts in the problem of image segmentation [8, 14, 15, 17]. They target at obtaining coherent pixel labelings by connecting forests to graphical models, adopting the latter as a post-processing stage [15, 17] or directly while growing the trees [8, 14]. By contrast, we aim to learn discriminative transitions between frames beyond temporally smooth labels.

In this work, we propose 'transition forests', an ensemble of randomized tree classifiers that learn transitions in a discriminative way. During training, we group frames that have similar associated transitions and class label. We formulate this into node splitting where we alternatively optimize the standard classification criterion of decision forests or the novel objective function for transitions. The latter is designed to decide the routing of single frames taking into account the route of their associated transitions pairs. In the end of tree growth, training frames arriving at the leaf nodes represent effectively a class label and associated transitions. Using single frame representations allows us to keep the feature representation simple and the inference complexity low.

1.1 Related work

Skeleton-based action recognition. Skeleton-based human action recognition is broadly tackled as a time series problem where the challenges include modelling the temporal dynamics of human poses. Generative models such as Hidden Markov Models (HMMs) [12, 21, 22] and Recurrent Neural Networks (RNN) [4, 18] have been proposed. [12] derive local features from individual and multiple joints, while [22] represents poses as 3D histograms of joints for training a HMM. [21] models the emission probabilities of hidden states in HMM using a deep forward neural network. [4, 18] show that using a RNN with Long-Short Term Memory (LSTM) better captures the long-term temporal information than a simpler RNN models [13]. Discriminative approaches have also been widely adopted. For instance, [20] extracts local features from body joints and their surrounding appearance information and captures temporal dynamics using Fourier Temporal Pyramids (FTP), further classifying the sequence using Support Vector Machines (SVM). Similarly, [19] represents the whole skeletons as points in a Lie group before temporally aligning sequences using Dynamic Time Warping (DTW) and applying FTP. [11] learns a dictionary using skeleton features and matches them using Temporal Pyramids. [26] proposes a moving pose descriptor from pose and its temporal derivatives and then mining temporally discriminative frames. While the previous methods are either generative or require feature vectors encoding motion information, we focus on a discriminative framework that learns dynamics as well as statics using per-frame representations.

Forests for classifying temporal data. There have also been a number of attempts to use randomized forests for action recognition. [5] directly stacks features from continuous frames and grows forests to classify them. Adding a temporal regression term, [2, 23] maps appearance and pose features to vote in an action Hough space. Also using a Hough framework, [6] computes histograms of the tree paths of consecutive pair of frames. Using the clustering properties of trees, i.e. leaf nodes, [24] constructs codebooks with the help of different heuristic rules capturing structural information. [3] propose Pairwise Conditional Random Forests (PCRFs) for facial expression recognition. They are an ensemble of trees of which split features operate on pairs of frames. Subsets of pairs of frames are formed to cover different facial dynamics and fed into classification forests, thus the prediction at testing is made using the whole sequences. By contrast, our method utilizes single frame representations: at testing, they are passed down the trees independently (thus being efficient and enabling online recognition), then pair-wise relations are obtained from the leaf nodes at which they arrive. Some generative methods based on forests include Dynamic Forest Models (DFMs) [9], which are ensembles of autoregressive trees that store multivariate normal distributions at their leaf nodes. These distributions model observation probabilities given short history of previous \( k \) frames. In a similar fashion to HMM, a model is trained for each action label and inference is performed maximizing likelihood of the observed sequence. Some relevant methods are compared in Section 3.

Tree-based methods for structured prediction. A related line of work utilizes decision forests for image segmentation where the objective is to obtain coherent pixel labels. [18] predicts pixel labels with a classification that are further smoothed with a Conditional Random Field (CRF), which learnt forest codebooks for both pixels and regions, using the latter as a prior information to smooth
Figure 1: Consecutive frames representing two different actions (in blue ‘duck’, in red ‘kick’) arrive at node 0. These frames are split in two different subsets $S_1$ and $S_2$ corresponding to child nodes 1 and 2 respectively. We compute the transitions as pairs of frames separated by $k$ time steps ($k = 1$ in this example) and we group them according to the route of each individual frame. $T^{1}_{1}$ and $T^{2}_{2}$ present only one transition, while $T^{1}_{2}$ two (one per class) and $T^{2}_{1}$ is empty. $T^{j}_{i}$ are determined by the split $\theta_0$.

individual pixel predictions. [14] proposes a CRF model where interactions between variables are modelled using a decision forest. [8] proposes to optimize the tree nodes using a CRF-like energy while encoding variable dependencies with the help of a geodesic distance. This distance is used as both the feature and pair-wise term of forest predictions. While the aforementioned methods focus on the coherency of predictions in an image space, our method tries to capture discriminative changes of data/prediction in a temporal domain.

2 Transition Forests

Suppose we are given a training set $S$ composed of different sequences of variable length $L$ as input-output pairs $\{(x_1, y_1), \ldots, (x_t, y_t), \ldots, (x_{L}, y_{L})\} \in \mathcal{X}^{L} \times \mathcal{Y}^{L}$. Each sequence is an action $y \in \mathcal{Y}$ performed by a human and represented by a succession of frames $x_{1:L}$ and our objective is to infer $y_t$ given for every $x_t$ using decision trees. On a decision tree, an input instance $x_t$ starts at the root and traverses different internal nodes until it reaches a leaf node. Each internal node $i \in \mathcal{N}$ contains a binary split function $f$ with parameters $\theta_i$, which decides whether the instance should be directed to the left or to the right child node.

Consider the set of nodes $\mathcal{N}_l \subset \mathcal{N}$ at a level $l$ of a decision tree (as shown in Figure 2). Let $S_i$ denote the set of labeled training instances $(x_t, y_t)$ that reach node $i$. For each pair of nodes $i, j \in \mathcal{N}_l$, we can compute the set of pairs of frames $T^{j}_{i}$ that travel from node $i$ to node $j$ in $k$ time steps as:

$$T^{j}_{i} = \{(x_{t-k}, y_{t-k}) \mid (x_t, y_t) \in S_i \land (x_t, y_t) \in S_j\}$$

where we term the set of pairs of frames $T^{j}_{i}$ as transitions from node $i$ to $j$. Note that $T^{j}_{i}$ depends on the frames that reached nodes $i$ and $j$.

Our motivation is illustrated in Figure 1. We observe that the decision $f(\theta_0, S_0)$ is quite good as it separates $S_0$ in two sets, $S_1$ and $S_2$, in which one action label predominates. If we examine the transitions associated to this split, we see that we obtain two pure sets, $T^{1}_{1}$ and $T^{2}_{2}$, one mixed set $T^{1}_{2}$ and one empty set $T^{2}_{1}$. Imagine now that we observe the ‘kicking’ frame in $S_1$ and we would have to make a decision based on this split, we would certainly assign the wrong label ‘duck’ with an uncertainty of $2/3$. Alternatively, if we also check the previous observed frame (in $S_2$) and inspect their associated transition $T^{2}_{1}$, the uncertainty is now $1/2$ and thus we would be less inclined to make a wrong decision.

From the above example, we deduce that if we had obtained a better split and both child nodes were pure label-wise, we would certainly make a good decision by only looking at child nodes. However,
Figure 2: Growing a level $l$ of a transition tree depends on all the decisions $\{\theta_i\}$ at the same time. Each $T^j_l$ divides in four disjoint sets according to the different routes that a pair of samples can follow.

Good splits are difficult to obtain if the temporal dynamics are not well captured on the feature space. On the other hand, if we had obtained a split that made transitions pure, we could also make a good decision. All these observations motivate our work and instead of only learning the splits to reduce the class uncertainty of individual frames we do so for the transition sets.

2.1 Learning Transition Forests

Our method for training a transition tree works by growing the tree one level at a time. At each level, we randomly assign to each node one splitting criterion, choosing between classification or transition. As for classification we utilize the information gain, commonly used for growing classification trees. The transition criterion is one of our contributions and it aims to learn the split features in a way that transitions between child nodes are directed to its related to a pair of child nodes. Note that this notation include self-transitions for pair of frames that reach the same node.

The objective function $E$ associated with the current level of the tree is a function of the set of transitions between child nodes $\{T^j_l\}_{i,j} \in \mathcal{N}_{l+1}$. Thus, the task of learning a level in our tree can be formulated as the joint minimization of the objective function over the split parameters $\{\theta_i\}$ as:

$$\min_{\{\theta_i\}} E(\{\theta_i\})$$

(2)

Objective function. We are interested in finding discriminative transitions between nodes. In other words, we want the transitions sets at the grown level to be more pure than in the previous level of the tree. For this, we propose as the objective function the weighted entropy of the transition sets:

$$E(\{\theta_i\}) = \sum_{i,j \in \mathcal{N}_{l+1}} |T^j_i| H(T^j_i)$$

(3)

Where $T^j_i$ is defined in $[1]$ and $i,j \in \mathcal{N}_{l+1}$ and $H(T^j_i)$ is the Shannon entropy of the class labels $y$ over the transition set $T^j_i$.

Optimization. The problem of minimizing the objective function (3) is hard to solve exactly as the decision in a node depends on the decision at other nodes. Our strategy to find the split function parameters $\{\theta_i\}$ associated to a level of the tree is presented in Algorithm 1. We start assigning a
Algorithm 1 Learning level $l$ of a transition tree

Input: Set of nodes $N_l$ at level $l$
Output: Set of split function parameters $\{\theta_i\}$

1: procedure LEARNLEVEL($N_l$)
2: randomly draw a fraction $\tilde{N}_l \subset N_l$ of nodes
3: optimize $N_l \setminus \tilde{N}_l$ using standard greedy procedure
4: initialize $\{\theta_i\}$ for $i \in \tilde{N}_l$
5: while something changes do
6: for all $i \in \tilde{N}_l$ do
7: $\Theta \leftarrow$ random feature and threshold selection
8: $\theta_i \leftarrow \arg \min_{\theta \in \Theta} E(\theta_i \cup \{\theta_j\}_{j \in \tilde{N}_l \setminus \{i\}})$
9: end for
10: end while
11: end procedure

A fraction of nodes to be optimized using the greedy procedure and the rest with the proposed transition objective function. For the transition nodes, we iterate over every node to find the split function that minimizes the objective function while keeping the rest of the nodes fixed. The initialization of the transition nodes and the order of the iteration is important. We found that initializing the nodes using the greedy procedure produced lower objective function values after optimization than a random initialization. The same effect was found when giving a priority to nodes with a higher number of training samples. Using this procedure it is not likely to reach a global minimum, but in practice we found that is effective at minimizing our objective.

2.2 Inference

Restricting ourselves to the set of leaf nodes $L$, we assign each transition subset $\{T^j_i\}_{i,j \in L}$ a conditional probability distribution over class labels, denoted $\pi^j_i(y_t)$ and named transition probability. This is different from standard decision forests where the probability distribution $\pi_i(y_t)$ is estimated over all the set of training instances $S_i$ that reached the leaf node $i$. Instead, we focus on subsets of transitions that depend on which node their respective previous $k$ frame reached. For an ensemble of $M$ transition trees we define a prediction function given two frames and temporal order $k$:

$$p_k(y_t | x_t, x_{t-k}) = \frac{1}{M} \sum_m \left( \pi^j_i(x_{t-k}) \right)^{(m)} \left( \pi^j_i(y_t) \right)^{(m)}$$

(4)

where $\ell(x_t)$ and $\ell(x_{t-k})$ are the leaf nodes reached by $x_t$ and $x_{t-k}$ at $m$-th tree respectively.

We combine the above probability with the standard prediction of the forests:

$$p(y_t | x_t) = \frac{1}{M} \sum_m \left( \pi_{\ell(x_t)}(y_t) \right)^{(m)} \frac{1}{k_{\max}} \sum_{1 \leq k \leq k_{\max}} p_k(y_t | x_t, x_{t-k})$$

(5)

Note that equations 4 and 5 can be also computed for a standard classification forest by simply passing the training set through the forest and estimating the function $\pi^j_i(y_t)$. If the training data is not enough, we can have empty transition subsets $T^j_i$. For this reason we set a minimum number of instances $n_{\min}$ needed to estimate their probability function. This parameter is conceptually the same as the stopping criterion of requiring a minimum number of samples to split a node in a decision tree. In these cases, we go up on the tree and we estimate the histogram between the first parent nodes that have a number of transitions over $n_{\min}$. Furthermore, in the case of unbalanced trees, if two leaf nodes are at different levels, we compute their histogram only between the lowest level nodes.
3 Experiments

Datasets and evaluation protocol. The evaluation is performed on MSRC-12 [5] and MSRAction3D [10] skeleton action recognition benchmarks. MSRC-12 consists of 12 iconic and metaphoric gestures performed by 30 different actors. To allow direct comparison with the results reported in [9], we follow their exact experimental setting detailed next. We only use the six iconic gestures, a total of 296 sequences of about 1000 frames each. We employ 5-fold leave-person-out cross validation, where each fold consists of 24 persons for training and 6 persons for testing. The observation vector \( x_t \) consists in the \( xyz \)-coordinates of the body joints, resulting in a 60-dimensional feature vector. The performance metric is the average per class classification accuracy.

MSR Action3D is composed of 20 actions performed by 10 different actors. Each actor performed every action two or three times. We perform our main experiments following the setting proposed by [10]. In this protocol, the dataset is divided into three subsets of eight actions, named AS1, AS2 and AS3. The training set consists of samples from subjects 1,3,5,7,9 while the rest are used testing. For comparison with other approaches, we will also show our best result with the protocol from [20] in which all 20 actions are used and the subjects are assigned to training and testing as in the previous setting. We use a very simple feature function inspired by [21, 27]: \( x_t = [\phi_j, \phi_m, \phi_o] \), where \( \phi_j \) is the difference between pair of joints at current \( t \), \( \phi_m \) and \( \phi_o \) the the difference between joints from current \( t \) to \( t-1 \) and \( t = 1 \) respectively. Note that this descriptor encodes very atomic motion information, only between two consecutive frames. In our implementation we obtain a 627-dimensional feature vector for each frame. The performance metric is the average classification accuracy over the three subsets.

In all the forest-based experiments, baselines included, we fix as forest parameters a number of trees of 12 and maximum depth 10 in the case of MSRC-12 and 50 trees of 8 depth for MSRAction3D.

Discriminative power of learned transitions. First, we measure the performance of our learned transitions by breaking down the terms of equation[5]. We run two different experimental settings corresponding to a standard decision forest, denoted as RF, which has been trained using the standard classification procedure and a transition forest trained with the new presented procedure, denoted as TF. For the TF, we train one forest for each temporal order \( k \) of the transition. For each classifier, we show the performance by: (i) using only the standard forest classification term; (ii) using only the transition probability as in equation[4]; (iii) combining both terms as in equation[5].
On Figures 3 and 4 we present the results for MSRC-12 and MSRAction3D respectively. For the latter we only show the results on subsets AS1 and AS2, as on AS3 we obtain the same result of 97.3% for all transitions (in both RF and TF) and 96.1% for RF in classification setting. This suggests that actions from subset AS3 are well represented using only static information.

The results clearly show that learning transitions instead of just estimating them on the RF has a large impact on the results. We observe that learning transitions also helps to increase the standard classification accuracy. This means that splitting the nodes using the transition criterion helps to separate classes on the feature space by introducing temporal information that was not available otherwise. Combining the transitions with the classification term increases the overall performance on MSRC-12. However, this is not the case on MSR Action3D where combining both predictions tends to produce worse results in all experiments than using only transitions. This is due to the fact that classification predictions perform poor, specially on the AS2 subset which is the subset with most challenging temporal dynamics that are not well captured in our descriptor. Using a smarter combination of both transition and classification predictions may lead to better results. Note that the setting (iii) using RF and $k = 1$ is conceptually similar to the Hough transition histogram from [6], however our approach is different as our transitions are learned and we estimate the probabilities in a different way.

Comparison with baselines. On tables 1 and 2, we compare our transition forest with three forest-based baselines for different temporal orders $k$. As our first baseline, we implement a decision forest using the sliding window (SW) setting [5] in which the temporal order is relative to the size of the window, with $k$ the number of stacked previous frames. This baseline allows us to compare how our algorithm can deal with temporal dynamics without increasing the complexity of the feature space. In order to assess the discriminative power of our transitions, our second baseline is a pairwise forest similar to the one used for facial expression recognition [3]. Our implementation consists in the concatenation of $k$-distant pairs of frames and learning a decision forest to classify them. To compare our discriminative method with a generative forest method, our third baseline is the Dynamic Forest Model (DFM) [9] where $k$ is the order of their non-linear Markov model. As there is not a public implementation available, we directly report their original results on MSRC-12. To put the reader into perspective, the results provided by [9] for two classical time-series algorithms, HMM and DTW, were 84.4% and 81.1% classification accuracy respectively. On MSRAction3D we show the averaged result over the three subsets of actions.

From the results, we observe that our approach performs better than all the baselines on both datasets. Among baselines, the sliding window approach tends to perform worse than the rest. Taking into account that the input window is the same as in DFM, the latter performs much better mainly to their generative modeling of time. Our approach shows better performance by only using a single frame representation, meaning that our forest is able to capture temporal information without the necessity of augmenting the feature space. On the other hand, growing a pairwise forest is more effective than using a sliding window setting, meaning that forest is able to better capture discriminative information between pairs of frames rather than longer temporal variations. Our forest is able to learn this information in a more effective way than pairwise forest, which shows the suitability of our learning method.

Comparison with the state of the art. We conclude our experimental evaluation with the comparison against the state of the art on both datasets. For the MSRC-12 dataset, we obtain a performance of 92.2% which is higher than the 90.9% from the DFM as we saw on the baselines comparisons. To the best of our knowledge, only [7] showed a better performance of 96.8% by using a much elaborated feature descriptor. Note that for this dataset we only used raw features and there is still room to improvement by using other feature representation with our transition forest.
Table 3: MSR Action3D: Comparison to state of the art.

| Method          | AS1 | AS2 | AS3 | Average |
|-----------------|-----|-----|-----|---------|
| BoF forest [27] | -   | -   | -   | 90.9    |
| Lie group [19]  | 95.3| 83.9| 98.2| 92.5    |
| RNN+LSTM [4]    | 93.3| 94.6| 95.5| 94.5    |
| Ours            | 94.3| 84.8| 97.3| 92.1    |

For the MSRAction3D dataset (see Table 3), our best result is an average of 92.1% using the protocol from [10]. This is comparable to the result obtained by [19], even if they use a much elaborated feature descriptor. Less favorable to ours is the result reported by [4] of 94.49%. Although we outperform their results on AS1 and AS3, their excellent performance on the most challenging subset (AS2) makes their approach the current state of the art. Interestingly, we obtain better results than [27] using their same skeleton representation and decision forest, however we do not perform a bag of features approach as theirs. Using the setting from [20] we obtain an accuracy of 86.0%, which is considerably better to the 82% reported by [21] using the same frame representation as ours jointly with a HMM and a deep forward neural network but far from the state of the art for this setting of 92% using RNN+LSTM [18].

Efficiency. Using single frame representations allows us to obtain performance comparable to a decision forest. Computing transition probabilities only requires to access one variable using the current leaf node and the previous one, thus only needing one tree prediction per frame. Using 50 trees of depth 8 and $k = 3$ we can predict one sequence of 100 frames in less than 10ms with a common laptop (Intel Core i7-6700HQ 2.6 GHz and 16GB RAM) and without any form of parallelization.

4 Conclusion

We proposed a new forest based classifier that is able to learn transitions in a discriminative way. Learning transitions using our technique helps to capture the temporal dynamics in a better way than in common approaches using decision forests classifiers. Despite using very simple frame descriptors, we obtain results comparable to state of the art with a high efficiency. As a future work, we plan to investigate different ways of combining the classification and transition probabilities as well as trying more powerful feature descriptions.

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