Random Pairwise Shapelets Forest

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Abstract. Shapelet is a discriminative subsequence of time series. An advanced
shapelet-based method is to embed shapelet into accurate and fast random for-
est. However, it shows several limitations. First, random shapelet forest requires
a large training cost for split threshold searching. Second, a single shapelet pro-
vides limited information for only one branch of the decision tree, resulting in
insufficient accuracy and interpretability. Third, randomized ensemble causes
interpretability declining. For that, this paper presents Random Pairwise Shape-
lets Forest (RPSF). RPSF combines a pair of shapelets from different classes to
construct random forest. It omits threshold searching to be more efficient, in-
cludes more information for each node of the forest to be more effective. More-
over, a discriminability metric, Decomposed Mean Decrease Impurity (DMDI),
is proposed to identify influential region for every class. Extensive experiments
show RPSF improves the accuracy and training speed of shapelet-based forest.
Case studies demonstrate the interpretability of our method.

Keywords: time series classification; shapelet; random forest; interpretability

1 Introduction

Time series is ubiquitous. It is produced everyday and everywhere in real world, such
as ECG recordings, financial data, industrial observations, etc. Time series classifica-
tion is an important subject in the field of data mining. Unlike general classification
tasks, it takes attribute order into account. Recent studies have shown that the 1NN
with dynamic time warping (DTW) remains among the most competitive classifica-
tion approaches [1]. However, this method has drawbacks of high classification time
complexity and lack of interpretability.

Shapelet is the most discriminant, phase independent subsequence in time series
[2]. It is proposed to detect phase-independent localized similarity within the same
class. In preliminary works, researchers use various methods to extract shapelet, and
to embed it into decision tree directly. The shapelet-based approach has the following
characteristics. First, shapelet shows local features, which is its main difference from
1NN. Second, since only the comparison with shapelet is needed, it is not only faster
in the classification stage, but also needs less storage space. Third, shapelet figures
out the key points of classification process and provides better interpretability. Never-
theless, this method suffers low accuracy and slow training process though several
acceleration strategies are raised [3] [4].
Random forest can achieve good performance through integrating a series of modest classifiers [5]. Shapelet-based random forest has attracted significant attention and research effort recently. Renard et al proposed a method of randomly extracting shapelet to build decision trees [6]. Karlsson et al introduced random shapelet forest. It selects both training instances and shapelet candidates randomly [7]. Experiment shows that effective result can be achieved when the amount of selected shapelet candidates is less than 1% of the full set, which greatly saves time. In response to the interpretability decline caused by randomization, a contribution metric Mean Decrease Impurity (MDI) is introduced [8]. Random shapelet forest has also been extended to multivariate time series forest, applied successfully to ECG classification [9] and early classification problem [10]. Deng et al proposed employing a combination of entropy gain and distance measure to evaluate the node split in forest [11]. Cetin et al proposed a shapelet discovery technique that allows efficient candidates evaluation in multivariate time series forest [12].

However, some shortcomings can be seen in shapelet forest. First, a single shapelet often cannot provide enough information to distinguish different classes. Second, a time-consuming split threshold searching is needed to evaluate candidate shapelet. Third, randomization and ensemble lead to interpretation declining easily.

For these challenges above, this paper proposes an ensemble algorithm that combi

Fig. 1. (left) Classic shapelet tree structure; (right) Pairwise shapelets tree structure.
(2) Faster. RPSF no longer needs to find the split threshold, which saves computing resources. This is especially true when introducing entropy early pruning to speed up [2] (constantly evaluating shapelet under limited information and abandoning apparent inadequate candidates in advance).

(3) Better interpretability. RPSF provides better interpretability at two levels rather than existing methods.

First, each individual decision tree has better interpretability. We extract information for both sides of the binary decision tree. This is beneficial for researchers to understand the profound mechanism of model.

Second, the Decomposed Mean Decrease Impurity (DMDI) proposed to illustrate the importance of each attribute provides better interpretability for RPSF. This method evaluates the contribution of each time series attribute for each class, and considers those with higher scores hold better discrimination. Existing MDI provides only a global score, which is determined by its tree structure [8]. On the contrary, the proposed tree structure allows us to decompose the contribution into different classes. Fig. 2 shows results of the two methods on ECGFiveDays dataset, both methods point to similar subsequences (red), while the DMDI method also indicates additional discriminant sequences (blue) for the other class. This result is in line with medical conclusion (see [13]). In Section 5, we will further discuss the performance of DMDI on other datasets.

![Fig. 2.](left) Existing MDI interpretation; (right) our DMDI interpretation. Both from ECGFiveDays dataset. The right one indicates discriminative features for both classes.

The remainder of the paper is organized by the following. In the next section, we present RPSF algorithm in detail. Section 3 explains the DMDI forest interpretation method. In Section 4, the experimental setup and results from the empirical investigation are described. Case studies are shown in Section 5. Finally, we summarize the main contributions and discuss future work in Section 6.

2 Random Pairwise Shapelets Forest

RPSF trains multiple pairwise shapelet-based trees to build an ensemble model, we will provide a detailed elaboration to the proposed algorithm in this section.
2.1 Providing more information by combination

Shapelet-based decision tree makes decision according to subsequence distance between instance and shapelet. It can be summarized as follows. If the instance is similar with shapelet (the subsequence distance is less than the split threshold) from a specific class, it is assigned to that class. If not, assigned to another class. However, similarity with features (shapelet) from only one class often cannot accurately characterize the information in the data. Just as each branch of a traditional decision tree indicates the splitting attribute value under the branch, we also hope that each branch of shapelet tree clearly shows what the current branch means. Under this notion, we propose the idea of combining a pair of shapelets from different classes in a decision tree, so that "like and not like" becomes "like A or like B". Decision can be made according to distances to the two shapelets in the pair rather than distance to a single shapelet and a threshold. This improves the accuracy of the classifier due to the additional information. Besides, diversity of the ensemble model can be improved since pairwise combination has more possible candidates than single one. At the same time, this idea also allows researchers to more clearly realize the basis of node division.

Pairwise-based method also has advantage in terms of training time cost. Because of the combination, the split threshold calculation, which is a significant time overhead, is omitted. This is especially true with introduction of entropy early pruning, where the previously calculated distance information can be reused, but the split thresholds, which is avoided by RPSF, must be recalculated each time.

2.2 Proposed Algorithm

RPSF trains a set of trees by taking several parameters: the shapelet length interval \( l, u \), the number of decision trees \( p \), and the number of candidate shapelets pairs in tree node \( r \). For each tree, we use a Bootstrap sample to generate a training set and construct the decision tree on the sampled dataset.

\[
\text{Algorithm} \quad \text{RandomPairwiseShapeletsTree}(D, l, u, r)
\]

**Input:** training set \( D \), lower shapelet length \( l \), upper shapelet length \( u \), number of trees \( p \), number of inspected shapelets pair \( r \).

**Output:** Pairwise Shapelets Tree \( ST \).

1: if IsTerminal(\( D \)) then
2: return MakeLeaf(\( D \))
3: \( S \leftarrow \emptyset \)
4: \( \text{for } i=1 \text{ to } r \text{ do} \)
5: \( S \leftarrow S \cup \{ \text{SampleShapeletsPair}(D, l, u) \} \)
6: \( (s_1, s_2) \leftarrow \text{BestShapeletsPair}(D, S) \)
7: \( (D_1, D_2) \leftarrow \text{Split}(D, s_1, s_2) \)
8: \( ST_L \leftarrow \text{RandomPairwiseShapeletsTree}(D_1, l, u, r) \)
9: \( ST_R \leftarrow \text{RandomPairwiseShapeletsTree}(D_2, l, u, r) \)
10: return \( \{(s_1, s_2, ST_L, ST_R)\} \)

The algorithm above shows the process of training each pairwise shapelets tree. At the beginning, the creation of leaf nodes is determined according to whether the data
is pure enough (entropy < 0.1) (lines 1-2). Then subsequences are extracted randomly from two random classes \(r\) times to form a candidate set. To be accurate, two time series are randomly selected from two randomly selected classes, then two lengths and starting points are randomly selected to form a pair of shapelets: \(s_1\) and \(s_2\) (lines 4-5). After that we assess candidates and find the best pair (line 6, details in next paragraph). The best pair \((s_1, s_2)\) is used to split the dataset \(D\) to two subsets \(D_1\) and \(D_2\).

Since there is no split threshold, we calculate the distances between a training instance \(D[m]\) and \((s_1, s_2)\) as \(d_1, d_2\). If \(d_1\) is less than or equal to \(d_2\), it means that \(D[m]\) is closer to \(s_1\), and \(D[m]\) is added to \(D_1\), otherwise \(D[m]\) is added to \(D_2\) (line 7). Finally, the algorithm recursively calls itself on \(D_1\) and \(D_2\) to construct subtrees (lines 8-10).

Information gain and split interval are typically used when shapelet assessment is needed [7]. For a shapelets pair \((s_1, s_2)\), we try to split training data by calculating the subsequence distance between training instance and \(s_1, s_2\) separately, and assigning each instance to its closer side (similar with splitting process in previous paragraph). When this process completed, information gain and split interval can then be calculated for this partition as a measure of the quality of the pair. A pair with greater information gain and split interval is considered preferentially. Entropy early pruning is introduced in this process to abandon apparently inadequate candidate [2].

After training, each internal tree node consists of a shapelets pairs \((s_1, s_2)\) and the left, right subtree. The leaf node records the class value. To classify a test instance \(T\), we begin from the root node. If the distance between \(T\) and \(s_1\) is less than the distance between \(T\) and \(s_2\), the left subtree is recursively used. Otherwise, the right subtree is recursively traversed. The process runs repeatedly until it reaches a leaf node and gets a prediction. We have \(p\) trees, the final result is obtained by majority voting.

### 3 Decomposed Mean Decrease Impurity

The main advantage of shapelet-based decision tree is its interpretability. However, it is eroded by randomized ensemble since the interpretation of each tree is different or even contradictory. To solve this problem, we define an attribute contribution scoring strategy for pairwise shapelets forest. Compared with existing method in [8], the improvement is that thanks to the tree structure of RPSF, attribute scores for each class could be explored so that discriminative patterns could be discovered.

We decompose all node’s information gain according to shapelet’s contribution (Equation 2), then add the contribution to attributes that form the shapelet. For shapelets pair \((s_1, s_2)\), if the dataset attracted by shapelet \(s_1\) cause greater entropy reduction (Equation 3), then it is assumed that \(s_1\) contributes more. Contribution of different classes’ shapelet is accumulated respectively. Based on the above idea, we define DMDI. Given pairwise shapelet forest \(R = \{ST_1, ST_2, \ldots, ST_n\}\), where \(ST\) is a pairwise shapelet tree. Each tree has multiple nodes, each node corresponds to a shapelets pair \((s_1, s_2)\). Given a training set \(D\) with series length \(m\), for time series attribute \(k\) and class \(c\), Decomposed Mean Decrease Impurity \(\text{DMDI}(k, c)\) is defined as follows.

\[
\text{DMDI}(k, c) = \sum_{u} \left( \sum_{\text{node}} (k_{\text{attr}}(s_1) > c) CV(\text{node}, s_1) + \sum_{\text{node}} (k_{\text{attr}}(s_2) > c) CV(\text{node}, s_2) \right) \tag{1}
\]
where $CV$ is the contribution value of one shapelet. It is obtained from the decomposition of total information gain of the node. Let the dataset that inputted to the node be $D_0$, the dataset obtained by dividing the $D_0$ be $D_1$, $D_2$. Assume $I_{(s_1,s_2)}(D_0)$ is information gain of the tree node, then

$$CV(\text{node}, s_i) = \frac{ER(\text{node}, s_i)}{ER(\text{node}, s_i) + ER(\text{node}, s_j)} \times I_{(s_1,s_2)}(D_0)$$

(2)

$$ER(\text{node}, s_i) = E(D_0) - E(D_i)$$

(3)

where $E(D)$ is $D$’s entropy, $ER(\text{node}, s_i)$ is the entropy reduction caused by a shapelet. We cannot guarantee that $ER$ is positive. It is set to zero in negative case. If the two terms in denominator are both zero, the node is discarded.

For every class, DMDI searches all nodes that embed a shapelet from it, decomposes the information gain of these nodes, and adds the contribution of shapelet to attributes forming it. Eventually we recognize which attributes in the sequence contribute more for a particular class.

4 Experiment and Evaluation

In this part, we experimentally evaluate the performance of proposed RPSF algorithm in terms of accuracy and time consumption. Source code of our experiments can be found at [14].

4.1 Experimental Setup

We select 43 datasets for experiments. All of them are UCR datasets and are widely used in studies. We discard datasets that cannot finish 10 times training in 48 hours.

Several algorithms are used for comparison. The nearest neighbor method (1NN) is a widely-used benchmark whose performance can be improved with DTW (DTW1NN). We also include Euclidean distance based nearest neighbor (ED1NN). The ShapeletTree (ST) algorithm is a classic shapelet-based method proposed in [2]. FastShapelet (FS) refers to the decision tree algorithm proposed in [13] where getting the approximate shapelet quickly through SAX. LearningShapelets (LTS) is an algorithm proposed in [15] that search shapelet by using optimization approach. gRSF is the state-of-the-art shapelet-based random forest algorithm proposed in [7].

For parameter settings, shapelet length interval of ST, gRSF, and RPSF are set to 25% to 67% of the total length of corresponding time series, which covers a larger range and is a relatively safe value. The number of decision trees for the latter two algorithms is set to 50. The number of candidate pairs in each node is set to 1% of the possible candidate shapelets. For algorithms involving randomization, the results are the average of ten runs.
4.2 Predictive Performance

In this section, we demonstrate that RPSF is competitive in term of classification accuracy compared to state-of-the-art algorithms in literature.

We first compare RPSF to single tree based algorithms, ST, LTS, and FS. Since ST and LTS are time consuming, we just finish the experiment on 22 relatively small datasets. Fig. 3 shows the results of this experiment and the average accuracy of each classifier. Ensemble based and nearest neighbor algorithms are faster, we compared the performance of RPSF, gRSF, and 1NN on 43 datasets. Fig. 4 gives the accuracy comparison of those classifiers. The area bellows the diagonal line indicates that RPSF is better.

![Fig. 3. Accuracy of RPSF compared with FS, LTS and ST](image)

In Fig. 3, the two methods, LTS and RPSF, show outstanding performances. Although LTS performs better on a large proportion of the data sets (13 of 22), its advantages are not obvious. In contrast, as we can see that three points at the lower triangular area of Fig. 3 (middle) are far away from the line, indicating that RPSF shows overwhelming advantage on these datasets. For example, it is 20.8% higher than the LTS on the OliveOil dataset, and 20.7% higher on the Wine dataset. Therefore, due to the advantage in average accuracy rate, RPSF overtakes LTS to be the best algorithm in this experiment. This experiment suggests that, when processing classification tasks, RPSF should be considered as a prior selection.

![Fig. 4. Accuracy of RPSF compared with gRSF, DTW1NN and ED1NN](image)

Fig. 4 gives results of the two random shapelet forest methods as well as 1NN method. RPSF achieves enhancement in two-thirds of the datasets (29 of 43) com-
pared to gRSF, and it is obviously superior to the nearest neighbor method on the vast majority of datasets.

Fig. 5 gives the critical differences diagram for the accuracy of individual algorithms ($p = 0.05$). Although LTS outperforms RPSF in term of ranking, there is no significant difference between them, and RPSF holds better average accuracy. RPSF beats other algorithms and is significantly better than FS, ST (tested on 22 datasets), and 1NN (tested on 43 datasets).

### 4.3 Computational Performance

Another advantage of RPSF is that it omits split threshold searching. This part shows the significant increase in time performance. Note RPSF approach is easy to parallelize, several times of further acceleration can be achieved using parallel computing.

**Versus other algorithms.** We compare RPSF with other time series classification algorithms in terms of training time. Since 1NN is a lazy algorithm, it is not included. Similar with previous settings, ST, FS, and LTS are tested on the smaller datasets, while shapelet-based forests are compared on 43 datasets. Parameter settings are the same as the previous one. Fig. 6 shows boxplots of the relative time consumption using RPSF as benchmark to make it more intuitive.

Fig. 6. Relative time consumption of LTS, ST, FS and gRSF compared with RPSF.
As you can see in Fig. 6, FS is faster than other methods, which is the major advantage of this approach. RPSF method is significantly better than ST and LTS on the vast majority of datasets. It even appears tens of times faster on some datasets. It is also noticeable that the single shapelet-based forest (gRSF) is slower than RPSF on almost all datasets. This result verifies our idea of omitting the calculation of the split threshold for time saving. In the next part, we will discuss it further.

**Stage Analysis.** This part divides RPSF and gRSF into two main stages and analyzes the time consumption of them. We will show that omitting split interval indeed save computation resources.

The decision tree of RPSF algorithm combines a pair of shapelets while gRSF is based on a single shapelet. In terms of time, the main difference is that while assessing candidates, on the one hand RPSF needs to calculate subsequence distances between two shapelets and all training instance, which is twice as much as that of single shapelet based method; on the other hand, in the process of evaluating a single shapelet, a split threshold needs to be found. This is omitted by RPSF. Note that with entropy early pruning [2], threshold searching will be executed multiple times during candidate assessment, while subsequence distance will only be calculated once since distance information can be reused. This expands the advantage of RPSF.

The process of evaluating shapelets is divided into two main parts: calculating subsequence distance and calculating information gain (used in threshold searching and candidate assessment). Table 1 selects several datasets that behave differently in terms of time performance and compares their relative time cost in the two parts.

| Dataset           | RPSF | gRSF | Total | RPSF | gRSF | Total |
|-------------------|------|------|-------|------|------|-------|
| Coffee            | 0.86 | 0.03 | 1     | 0.43 | 0.19 | 0.70  |
| CBF               | 0.74 | 0.14 | 1     | 0.36 | 0.98 | 1.48  |
| ECGFiveDays       | 0.67 | 0.10 | 1     | 0.62 | 1.18 | 2.15  |
| FaceFour          | 0.91 | 0.03 | 1     | 0.44 | 0.14 | 0.62  |
| ArrowHead         | 0.91 | 0.04 | 1     | 0.57 | 0.93 | 1.60  |
| GunPoint          | 0.86 | 0.07 | 1     | 0.42 | 1.41 | 1.87  |
| SyntheticControl  | 0.21 | 0.44 | 1     | 0.13 | 8.61 | 8.76  |

As the relative time cost shown in Table 1, the four bolded datasets particularly validate our hypothesis. RPSF’s distance computation consumes approximately twice as much as that of the gRSF, while the time spent for calculating information gain is apparently smaller. It is specifically noticeable on SyntheticControl dataset. For dataset ECGFiveDays, the time spent to compute subsequence distances does not conform to the hypothesis, which may be caused by entropy early pruning. It also indicates that in some cases the difference between the two subsequence distance calculations is trivial. In addition, it is clear that the time consumption of information gain on RPSF is obviously less than gRSF, and there is no doubt that RPSF is generally more efficient than gRSF, especially on relatively larger datasets.
5 Case Studies

As discussed in Section 3, the pairwise shapelets and DMDI enhance interpretability by providing explanation for each possible class. We briefly show the profit of DMDI on ECGFiveDays dataset in previous. More detailed real-world examples will be included to demonstrate the usefulness of our DMDI and RPSF model in this section.

5.1 GunPoint

GunPoint is a dataset that has been studied extensively in literature. The 150-length dataset describes the action curve of an actor with or without a gun when doing an action (as shown in Fig. 7). The key discriminant pattern for this dataset is around 100-120 time stamps. Since inertia carries actor’s hand a little too far and she is forced to correct it in Point case [2], in this location Point instances bear a slight dip, while Gun instances mostly do not. Another discriminant pattern is near 40-60 time stamps. Some of Point instances are relatively flat near this range, while all Gun instances are in rising state. This is because the actor can be more agile when she does not hold a gun [16]. The accuracy of RPSF on this dataset is 99.9%.

The DMDI metric is applied to the dataset, and the results are shown in Fig. 7. It is clear that the discriminant scores of the two classes arrive at their highest value near 100-120 time stamps, showing that our method succeeds in identifying the distinguishing features. This is consistent with the conclusion of [2] and [8]. In addition, the score of Gun reaches a local peak among the 40-60 indexes, it also matches the range of another discriminant pattern.

5.2 ArrowHead

Arrows classification is an important topic in archaeology. ArrowHead is a multiclass dataset with 251 attributes. Arrows can be divided into three classes according to their place, age, and the race belonged: Avonlea, Clovis, and Mix. Through starting from
arrow tip, moving round and recording distance to the centroid, the time series describes the outline of the arrows. Fig. 8 briefly depicts the series on the left part. The differences among these three arrows are that, the Clovis arrow has an unnotched hafting area near the bottom connected by a deep concave bottom end (near 125 time stamp), while Avonlea and Mix differ in a small notched hafting area connected by a shallow concave bottom end (near 90, 160 time stamp). These conclusions are confirmed by UCR anthropologists [2].

Our DMDI metric for this dataset is shown on the right side of Fig. 8. As described in the figure, Clovis peaks near 125 time stamp, and the other two peaks at 90 and 160 separately. It is obvious that shapelets pairwise forest and DMDI accurately capture the key points of real problem. In addition, for the multi-classification problem, existing MDI can only output a global solution, it cannot provide a subtle explanation for every class. This example fully illustrates the superiority of DMDI.

6 Conclusion and Future Work

In this paper, we present an effective and efficient random forest combining shapelets from different classes randomly. The model diversity, interpretability and classification accuracy are improved by including more information in a node. Due to the fact that pairwise shapelets do not have to search the split threshold, the time consumption is optimized. In addition, a novel forest interpretation method DMDI is proposed to evaluate the contribution of each attribute and to explain the proposed model. Extensive experiments and case studies show that our method outperforms state-of-the-art random shapelet forest.

The intuition of this model is to embed a pair of shapelets from different classes into a tree node, and to introduce more information for the classification. Although the random combination described is powerful, it is relatively simple. Trying to include a more sophisticated combination to further enhance the performance of random forest will be the focus of future work.
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