

MVSC-Bench: A Tool to Benchmark Classification Methods for Multivariate Spatiotemporal

Siddhant Kulkarni, Farnoush Banaei-kashani

Department of Computer Science and Engineering,
University of Colorado, Denver, CO, USA
{siddhant.kulkarni, farnoush.banaei-kashani}@ucdenver.edu

Abstract. Applications focusing on analysis of multivariate spatiotemporal series (MVS) have proliferated over the past decade. Researchers in a wide array of domains ranging from action recognition to sports analytics have come forward with novel methods to classify this type of data, but well-defined benchmarks for comparative evaluation of the MVS classification methods are non-existent. We present MVSC-Bench, to target this gap.

Keywords: Benchmarking, Multivariate Data, Spatiotemporal Data, Classification

1 Introduction

A *Multivariate Spatiotemporal Series (MVS)* dataset captures trajectories of several moving objects in a given space and timeframe. Each spatiotemporal source corresponds to one object, where objects can be birds in a flock, players in a sports team, vehicles in a transportation network or joints in human body. Figure 1 is an example of MVS dataset capturing human gait, where trajectories of same joints are visualized. Classification of MVS datasets has numerous knowledge discovery use cases such as gait identification [6], mobility analysis [2] and action recognition [1] from gait MVS as shown in Figure 1, traffic behavior analysis from traffic MVS and team tactic analysis from sports MVS. Several methods have been proposed for MVS classification, including solutions based on feature extraction [6], time series analysis [9], episode mining [10], etc. Despite the vast research interest in MVS classification (MVSC), reliable and generic benchmarks as well as tools to evaluate the effectiveness of new methods are non-existent. In turn, this results in confusion with respect to the transferability of approaches across domains, and therefore difficulty in choosing the appropriate methodology.

To fill this gap, in this paper we propose the demonstration of a benchmarking and evaluation tool, dubbed MVSC-Bench, which addresses three needs:

1. A benchmark for comparative analysis of the performance of existing MVS classification methods.
2. A standard for MVS data format as well as unified interface for MVS classification methods
3. A tool to evaluate performance of new MVS classification methods versus existing methods.

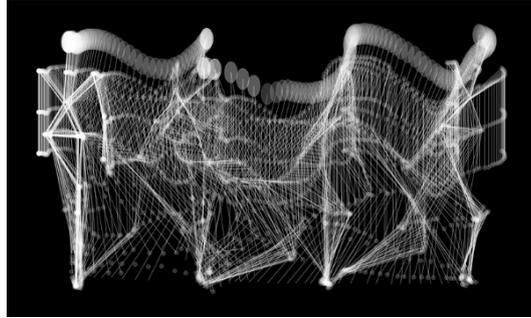


Fig. 1. MVS dataset capturing joint trajectories of human gait

The remainder of this paper is organized as follows. Section 2 presents the benchmark we have defined for MVS classification including datasets, benchmark experiments, and baseline classification methods. Section 3 describes MVSC-Bench system we developed to implement our benchmark and the challenges we addressed toward this end. Section 4 elaborates on our demonstration plan to showcase functionalities of the MVSC-Bench system.

2 Benchmark

Our benchmark is defined to evaluate performance of the MVS classification methods based on a variety of parameters including:

- Number of MVS datasets (e.g., human gaits) considered for training and testing
- Number of instances considered for each MVS dataset (e.g., number of gait instances for each human subject)
- Number of objects considered in each MVS data instance (e.g., number of joints considered for each gait MVS dataset)
- Any other method specific parameters (e.g., features to be extracted, type of similarity measure to be used, minimum support, etc.)

Users of MVSC-Bench can use these parameters to define a thorough and extensive set of benchmarking experiments to evaluate performance of various existing (and new) MVS classification methods. With MVSC-Bench we have also implemented two baseline methods for MVS classification to serve as reference for comparison (see section 3 for more details on baseline methods). The benchmark also defines standard interface that allows “plugging” in new methods to be compared with the baseline and other methods. The methods are compared based on the following measures: Accuracy, Time to train, Time to test and Memory required to save learning model. Moreover, our benchmark includes two sample MVS datasets, one capturing human gaits of over 140 humans with 4 or 5 instances of MVS data captured for each human walking across the view of a Microsoft Kinect [6] and the other one which records location of players in a soccer game which spans over 40 minutes capturing various spatial features of each player [8]. Our benchmark also defines a standard format that allows incorporating other MVS datasets in the benchmark.

3 System Description

MVSC-Bench is the demonstration system we have developed to implement our MVS classification benchmark. In this section, we briefly present components of the MVSC-Bench system. A video demonstration of MVSC-Bench is available online [11].

3.1 User Interface

MVSC-Bench supports two user interfaces: Graphical User Interface (GUI) and command line interface. With GUI (Figure 2), users interactively modify the parameters for experimentation. This mode allows users to experiment with baseline methods and allows for limited repeatability. The command line interface is for users who wish to create jobs to execute several experiments using established configuration files. Moreover, this mode allows users to customize the configuration file to include a new method or dataset. These two interfaces provide users with the flexibility to choose how to use MVSC-Bench based on needs and expertise level.

The screenshot displays the MVSC-Bench GUI with four numbered sections:

- (1) Dataset Path:** A text input field for specifying the dataset location.
- (2) Dataset Configurations:** A panel containing input fields for 'Number of objects for training' (10), 'Frame window step rate' (1), 'Total Number of Series' (15), 'Number of objects for testing' (2), and 'Number of instances per object for training' (2). It also includes a list box for selecting series (Series 1, Series 2, Series 3) and a note: '*NOTE: Please press CTRL and click on the series you want unselected'.
- (3) Classification Methods:** A panel with three main sections:
 - Feature Based Classification:** Includes checkboxes for 'Horizontal Range', 'Vertical Range', 'Mean Deviation of all the data points', and 'Standard Deviation of all the data points presented in data'. It also has radio buttons for 'Euclidean Distance' and 'Manhattan Distance'.
 - Time Series Similarity Based Classification:** Includes radio buttons for 'Euclidean Distance' and 'Dynamic Time Warping'. Below, it has radio buttons for 'First N frames' and 'Last N frames', with a note: 'Note: Here, N is minimum number of frames of 2 instances being compared'.
 - Pattern Mining Based Classification:** Includes input fields for 'Size of Sliding window' (20 frames), 'MinSupport' (10), and 'Grid Divisions' (X: 10, Y: 10, Z: 10 blocks).
- (4) Execution/Export/Import section:** A panel with an 'Execute Experiment' button, a 'File Path' input field, and three buttons: 'Export Results', 'Export Config', and 'Import Config'.

Fig. 2. MVSC-Bench GUI Sections: (1) Dataset path, (2) Generic Benchmarking parameters, (3) Approach specific configuration, and (4) Export/Import section

3.2 Baseline Methods

There are two baseline methods that have been embedded into the implementation of MVSC-Bench. The first approach is based on Feature Extraction [3-6] and it focuses

on extracting certain features from the data that will represent the multivariate spatiotemporal series for classification. These features are a generalization of the features specified in [6]. Once these features are extracted from given data, they are used to implement nearest neighbor classification.

The second approach is based on the idea of MVS Time Series Similarity analysis where entries for each individual variate is considered as a time series. The similarity between two MVS datasets is then evaluated by measuring similarity based on corresponding variates using Dynamic Time Warping (DTW) or Euclidean Distance and aggregating the pair-wise similarity of variates to compare similarity of MVS datasets.

3.3 Standard Plug-in Interface for New Methods

MVSC-Bench defines an “IApproachImplementation” interface which defines methods, their parameters and their return values that must be strictly followed by any method that is to be integrated with MVSC-Bench. This interface defines methods for training (where the new method should build the learning model), testing (where the learning model should be applied to one MVS dataset at a time) as well as two miscellaneous methods to retrieve the name of the approach and to write any information for the specific approach to a file.

3.4 Standard Data Format for New Dataset Integration

Finally, MVSC-Bench also defines a standard format that allows the integration of new MVS datasets into the benchmark. The format defines a folder structure where each MVS dataset (e.g. gait data for each individual) is stored in respective folders with the name of the folder indicating the class represented by the dataset. Each such folder may contain one or more text files that represent different instances of data. Figure 3 presents the format for an entry for each object of each instance of data stored.

Entry<M>Name;<X>;<Y>;<Z>;<Other Spatial Features separated by semicolon>

Fig. 3. MVSC-Bench Data Format for entries in each instance

4 Demonstration Plan

To demonstrate MVSC-Bench, we intend to use gait analysis as the focus application for demonstration. We will walk the audience through the following steps:

1. Explain the concept of MVS, MVSC and need of MVSC-Bench.
2. Present the users with gait based identification [2, 6] as an application of MVSC.
3. Present the user interface of the MVSC-Bench and its functionality.
4. Describe the command line interface provided for execution of experiments using a configuration file.
5. Elaborate the programming interface of MVSC-Bench defines to accommodate new methods.
6. Walk the audience through the process of using MVSC-Bench to integrate two new MVS classification methods.

- a. An extended feature based method that includes special features useful for gait analysis (e.g. stride length, gait cycle time, height of individual, etc.)
 - b. A new pattern based classification method (see below for more detail about this method).
7. Execute sample experiment and (while that executes) present the data format and how they can leverage it to add more gravity to their comparative study.
 8. Present and elaborate on the contents of the results.

In the remaining of this section we briefly describe the pattern based classification method mentioned above. This method extracts frequent patterns from MVS data. Each gait MVS dataset is then represented by the patterns derived from the dataset. Finally, in analogy with document classification, we consider each pattern as a word representing a gait dataset, and use TF-IDF [7] as similarity measure to classify MVS datasets.

References

1. J.L. Raheja, M. Minhas, D. Prashanth, T. Shah, A. Chaudhary, Robust gesture recognition using Kinect: A comparison between DTW and HMM, *Optik - International Journal for Light and Electron Optics*, Volume 126, Issues 11–12, June 2015, Pages 1098-1104
2. Farnoush B. Kashani, Gerard Medioni, Khanh Nguyen, Luciano Nocera, Cyrus Shahabi, Ruizhe Wang, Cesar E. Blanco, Yi-An Chen, Yu-Chen Chung, Beth Fisher, Sara Mulroy, Philip Requejo, and Carolee Winstein. 2013. Monitoring mobility disorders at home using 3D visual sensors and mobile sensors. In *Proceedings of the 4th Conference on Wireless Health (WH '13)*. ACM, New York, NY, USA,
3. Elena Gianaria, Marco Grangetto, Maurizio Lucenteforte, Nello Balossino. Human Classification Using Gait Features. *Biometric Authentication Volume 8897 of the series Lecture Notes in Computer Science* pp 16-27
4. Sinha and K. Chakravarty, Pose Based Person Identification Using Kinect, 2013 IEEE International Conference on Systems, Man, and Cybernetics, Manchester, 2013, pp. 497-503.
5. Ricardo M. Araujo, Gustavo Graña, and Virginia Andersson. 2013. Towards skeleton biometric identification using the microsoft kinect sensor. In *Proceedings of the 28th Annual ACM Symposium on Applied Computing (SAC '13)*. ACM, New York, NY, USA, 21-26
6. ANDERSSON, Virginia O.; ARAUJO, Ricardo M. Person Identification Using Anthropometric and Gait Data from Kinect Sensor. In: *Proceedings of the 29th AAAI Conference*. 2015
7. Ramos, J. (1999). Using TF-IDF to Determine Word Relevance in Document Queries
8. Svein Arne Pettersen, Dag Johansen, Håvard Johansen, Vegard Berg-Johansen, Vamsidhar Reddy Gaddam, Asgeir Mortensen, Ragnar Langseth, Carsten Griwodz, Håkon Kvale Stensland, and Pål Halvorsen. 2014. Soccer video and player position dataset. In *Proceedings of the 5th ACM Multimedia Systems Conference (MMSys '14)*. ACM, New York, NY, USA, 18-23.tS. Yu, T. Tan, K. Huang, K. Jia, and X. Wu, A study on gait-based gender classification, *IEEE Trans. Image Process.*, vol. 18, no. 8, pp. 1905–1910, August 2009
9. Michael D. Morse and Jignesh M. Patel. 2007. An efficient and accurate method for evaluating time series similarity. In *Proceedings of the 2007 ACM SIGMOD international conference on Management of data (SIGMOD '07)*. ACM, New York, NY, USA, 569-580.
10. Jiawei Han, Guozhu Dong and Yiwen Yin, "Efficient mining of partial periodic patterns in time series database," *Proceedings 15th International Conference on Data Engineering (Cat. No.99CB36337)*, Sydney, NSW, 1999, pp. 106-115.
11. Kulkarni, S. (2017). *siddhantkulkarni/MVSCclassification*. [online] GitHub. Available at: <https://github.com/siddhantkulkarni/MVSCclassification> [Accessed 26 Mar. 2017].