Data-Driven Activity Step Segmentation with Change Point Detection

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Introduction

- Project **builds** on ongoing work to monitor and assist older adults with daily activities in their homes by combining sensor technologies with machine learning and computer vision.
- We **propose** a method based on unsupervised change point detection to automate segmentation of activity data into individual steps to later track and prompt.
- We **hypothesize** that change point detection can be utilized to automatically segment activity video and wearable data.

Method

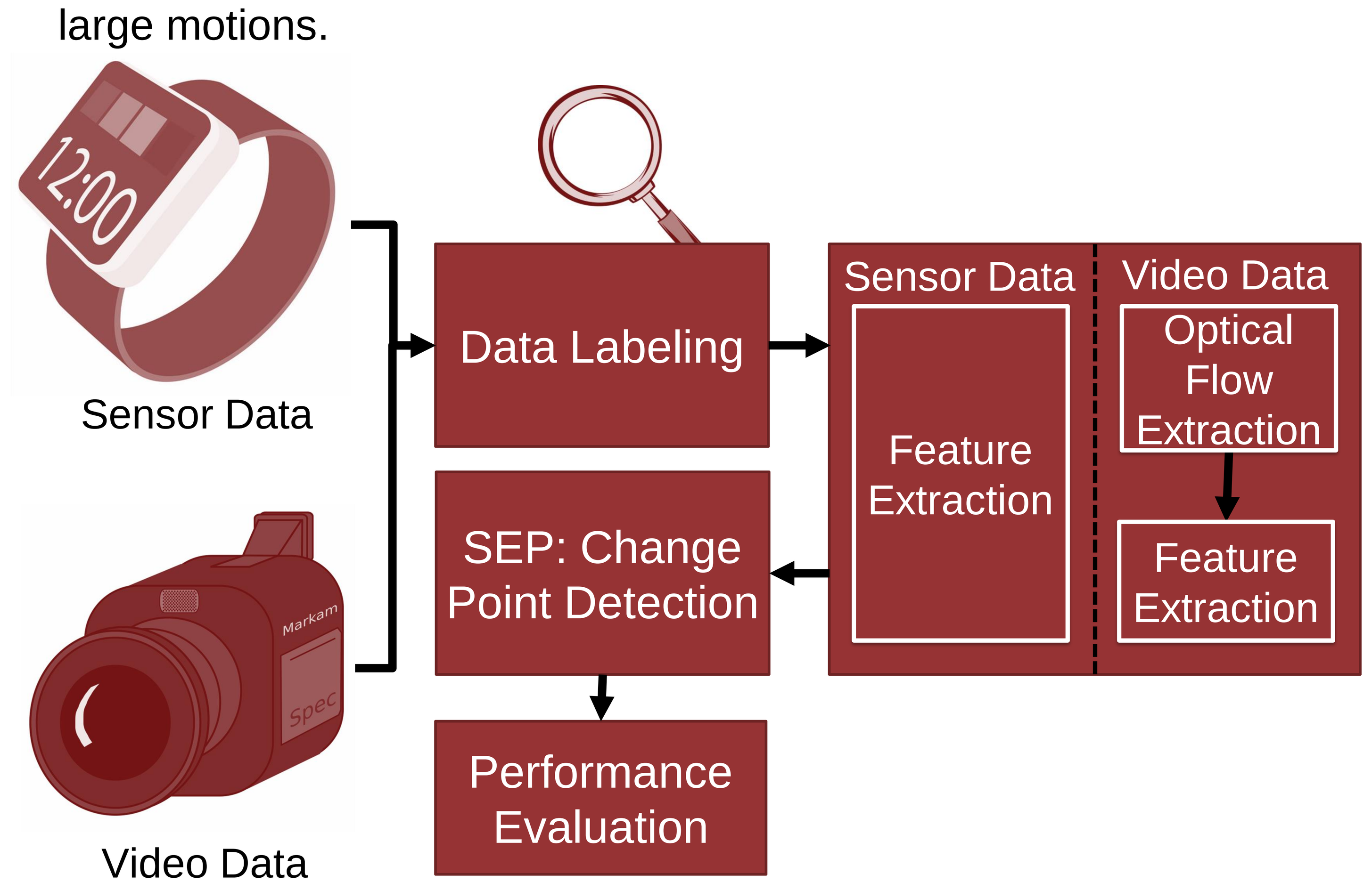
Experimental Design
- 13 participants
- 10 tasks reflecting Activities of Daily Living (ADL)

Data Collection
- Wearable data from Apple 3 Watch accelerometer and gyroscope sensors
- Video data from 6 cameras in smart environment

Movement Data Feature Extraction
- Wearable data statistical features
- Video data through optical flow algorithms and edge detectors

SEP Algorithm
- Considers each time *t* in time series data as a possible change point. Change points are scores above a threshold value that represent transition from one step to the next in an activity progression.

Video Processing Algorithms
- Edge Detector: Finds pixels or features that are optimal for tracking motion of objects using a tracking algorithm based on a model of affine image changes as well as a technique for monitoring features during tracking.
- Optical Flow: Calculates 2D displacement vectors showing the movements of points from one frame to the next using the Lucas-Kanade method along with pyramids which normalize small and large motions.



Sensor Data: Yaw, Pitch, Roll, Rotation (X,Y,Z), Acceleration (X,Y,Z)
Sensor Data Feature Extraction: Mean, Max, Min, Stdev, Range for 10 second window duration

Video Data: Optical Flow Vector Path Lengths
Video Data Feature Extraction: Mean, Max, Min, Stdev, Range for 100 frame window duration

Results

Results were generated for wearable data and video data on 5 activities performed by 13 participants. Wearable data for participant 13 exhibited compilation errors and was not included in the current results.

Evaluation Methods:
- Results were based on detected change points (DCP) versus ground truth change points (GTCP)
- Geometric means (Gmean)
- Confusion matrices: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) change points
- True Positive Rate (TPR), and False Positive Rate (FPR)

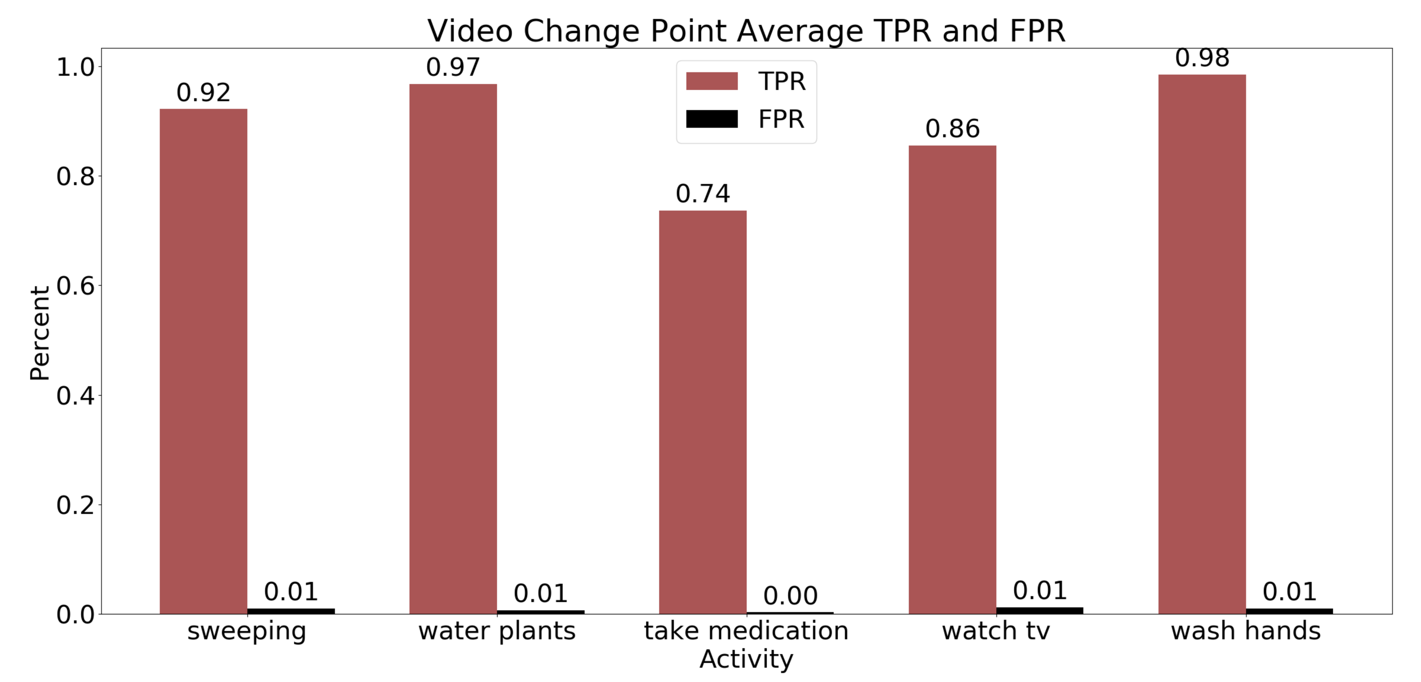
Wearable Data Results:
- The current approach failed to identify all ground truth change points, leading to skewed results.
- Resolution of this issue is necessary to identify whether false positive rates remain constant or reflect detection of ground truth change points that failed to be identified initially.

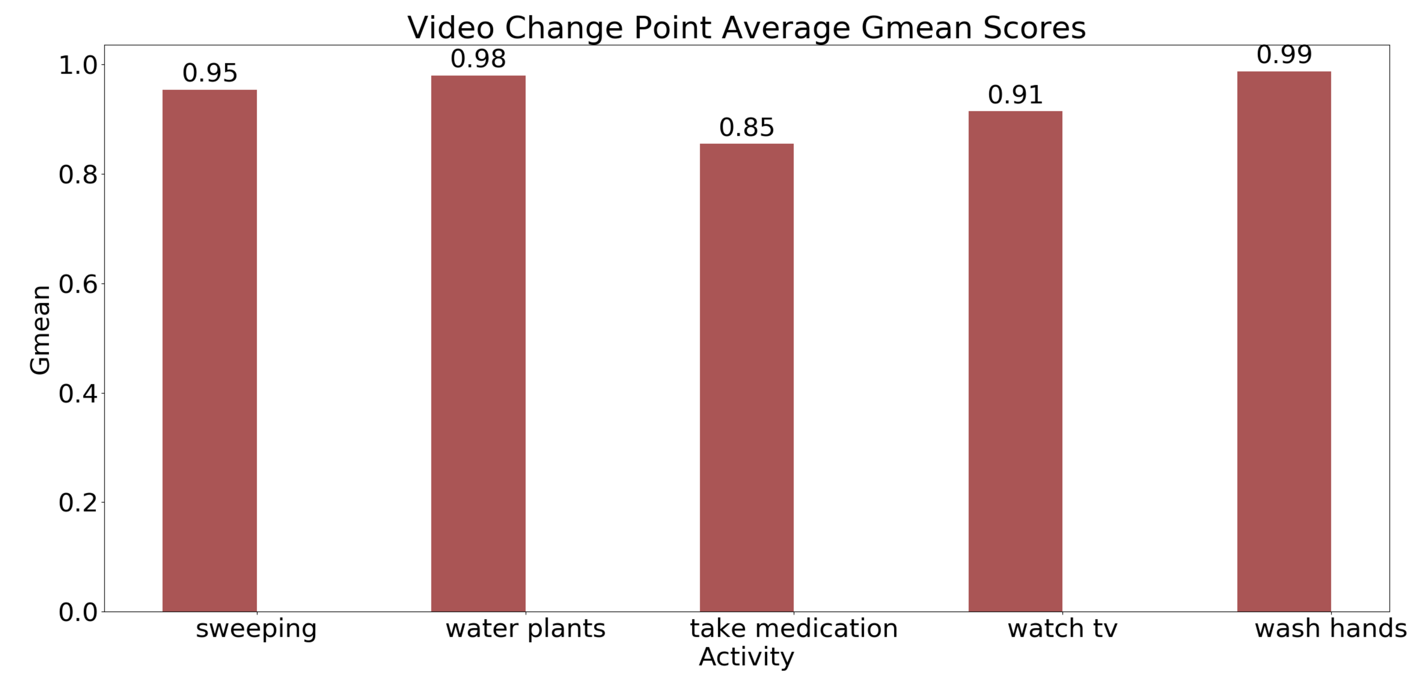
Wearable Data Results

Activity	GTCP	TP	TN	FP	FN	TPR	FPR	Gmean
Sweeping	6	1	4407	4.67	0	1	> 0.001	> 0.999
Take Medication	16	1	5940	6.75	0	1	> 0.001	> 0.999
Wash Hands	4	1	2404	2.42	0	1	> 0.001	> 0.999
Watch TV	5	1	2472	2.58	0	1	> 0.001	> 0.999
Water Plants	6	1	3361	3.5	0	1	> 0.001	> 0.999

*Figure 1: Shows average rates across 12 participants for wearable data.

Video Data Results:
- TPR's were high for most of the experimental trials with many having 100% detection rate.
- There were just as many if not more FP DTC compared to TP DCP.
- FNs were low overall with most being 0 or close to 0.
- Sweeping, Watering Plants, Washing Hands had very high TPRs and Gmean scores.
- Watching TV and Taking Medication had the lowest TPR and Gmean scores.
- All activities had average FPR of 1% or lower.





Discussion

Wearable Activity Segmentation:
- Increased change point labeling precision may lead to higher detection accuracies.
- Ground truth change point identification may benefit from adjusting the initial change point detection margin.

Video Activity Segmentation:
- Activities with more subtle step changes are more difficult to label and detect, such as take medication.
- Need higher frame rate recordings of activities for improved performance of SEP algorithm.

Limitations:
- Activity ordering effects
- Lack of interrater agreement for change point labeling
- Low frame rate reduces precision of labeling change points
- Video processing method can only extract motion data for one individual at a time

Conclusions

Impact
- Data-driven approach to activity segmentation with change point detection shows promising results.
- Need refinement for use with wearable data.
- Methods show promise for use in future automated prompting systems for individuals with memory impairment.

Future Work
- Integrate wearable and video data.
- Further evaluation in form of survey questions to judge third party perception of video segmentation results.
- Add ability to extract motion data of multiple people at a time in video processing method.
- Increase frame rate of video recordings.
- Label change points with input from more than one observer.

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