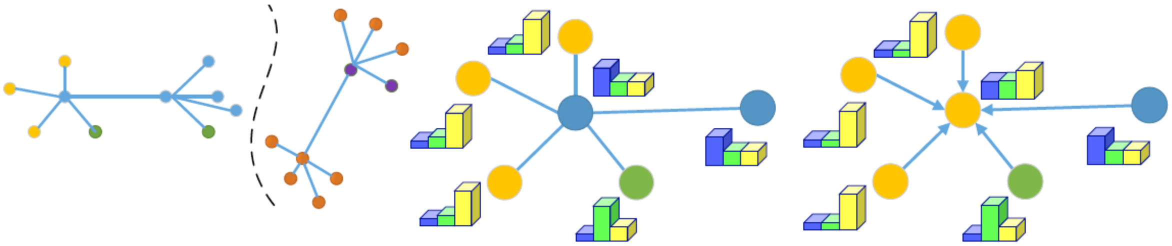
Synchronous Dynamic View Learning: A Framework for Autonomous Training of Activity Recognition Models using Wearable Sensors

Authors: Seyed Ali Rokni and Hassan Ghasemzadeh

Presented by: Abdullah Mamun

Date: 10 June 2026

Email: a.mamun@asu.edu



(a) Similarity graph examples (b) Distributions prior to propagation (c) Distributions after one step propagation

Paper **abdullah-mamun.com** ***𝕏: @AB9Mamun***

IPSN 2017 | DOI: 10.1145/3055031.3055087

The Challenge: Dynamic Wearable Settings

Wearable activity-recognition models can work well in controlled settings, but their accuracy can drop when the sensor setup changes in daily use.

The Core Problem

Dynamic environments: sensors may be added, removed, displaced, misoriented, replaced, or used by a new person.

Retraining burden: collecting enough labeled training data is time-consuming, labor-intensive, and expensive.

Autonomy gap: future wearables need to reconfigure their models without asking users to repeat the full labeling process.

1. Controlled Training

Sensor location and labels are known.

2. Real-World Change

New or moving sensor creates a new feature view.

3. Autonomous Learning

The system learns from synchronous observations.

Background: Wearable Activity Recognition

Wearables transform sensor streams into activity labels, but the signal patterns depend strongly on body location and sensor configuration.

Static View

Existing sensor with a trained activity-recognition classifier.

Example: ankle sensor trained in a controlled setup.

Dynamic View

New sensor with no labeled training data.

Example: phone or wearable moving between wrist, waist, and pocket.

Learning Goal

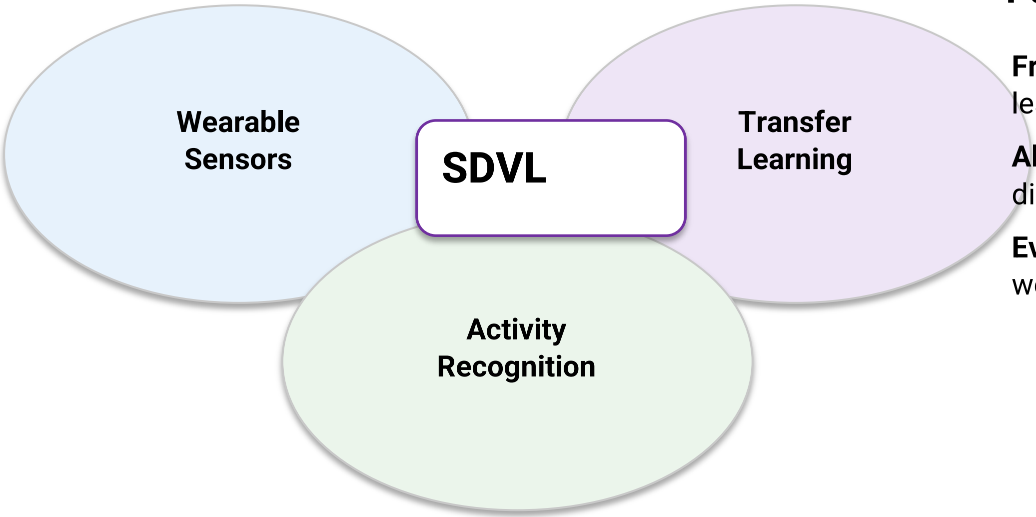
Use synchronous data to train the new sensor automatically.

No new ground-truth labels are required.

Focus of This Paper

Bridging the Gap: Autonomous Training Without New Ground Truth

The paper proposes Synchronous Dynamic View Learning (SDVL) to transfer activity-recognition capability from a trained static sensor to a newly added dynamic sensor.



Paper Contribution

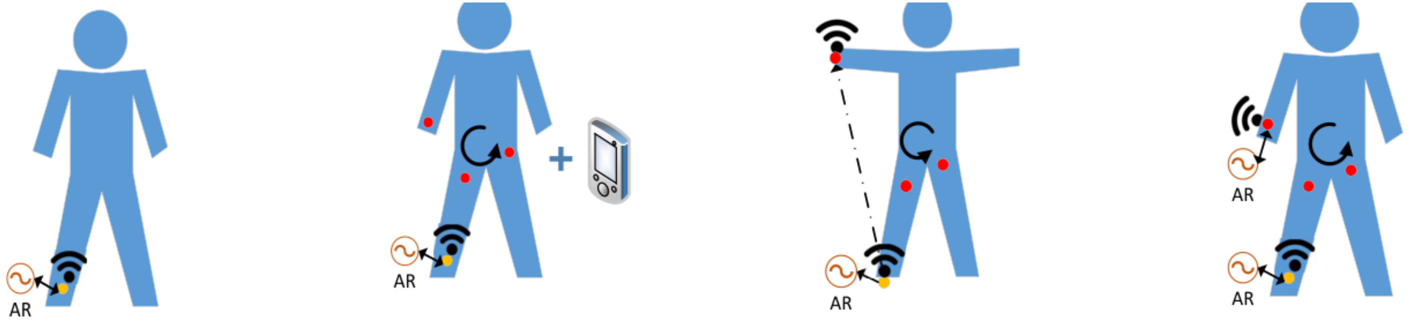
Framework: formalizes a dynamic-view learning problem.

Algorithm: uses semi-labels and minimum disagreement labeling.

Evaluation: tests performance on three wearable-sensor datasets.

SDVL Framework

The static sensor first acts as a teacher; the dynamic sensor learns its own classifier from synchronized observations.



(a) Initial Setting (b) Dynamic sensor addition (c) Autonomous learning (d) Collaborative recognition

Initial setting: a trained static sensor recognizes activities.

Dynamic addition: a new sensor can move across body locations.

Autonomous learning: semi-labels are refined to train the new sensor.

Collaboration: after training, both views can contribute to recognition.

Problem Definition: Label the Dynamic View

The dynamic sensor observes the same activities as the static sensor, but it does not have ground-truth labels for its own data.

Inputs

- A set of activities A
- Dynamic observations X
- Possible dynamic sensor placements
- Semi-labels from the static sensor

Challenge

The dynamic sensor has a different feature space and may move to different body locations during training.

Objective

Assign one activity label to each dynamic observation while minimizing the overall mislabeling error.

Core idea: transfer imperfect knowledge → refine labels using dynamic-sensor similarity → train a new classifier

How SDVL Works

SDVL does not simply copy the static sensor decision; it calibrates that decision with the dynamic sensor observations.

Static classifier

Predicts the current activity.

Semi-label

Sends a likelihood vector based on known confusion.

Similarity graph

Connects similar dynamic observations.

Refined labels

Uses propagation to train a dynamic classifier.

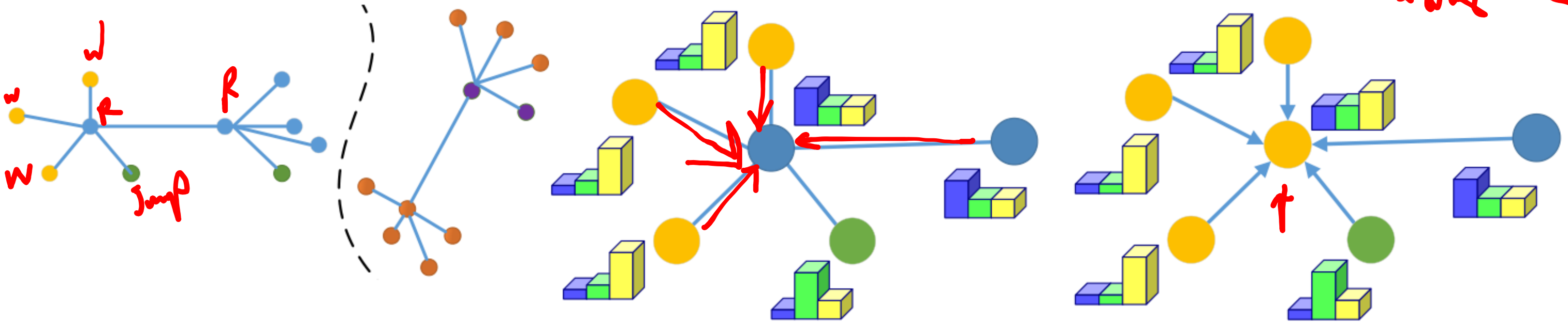
Semi-labels: a predicted activity plus a distribution over possible true activities.

Minimum disagreement labeling: similar observations should receive similar labels.

Iterative update: neighbor information is mixed with the original semi-label until the label distribution stabilizes.

Label Refinement with Similarity Graphs

The dynamic sensor uses its own feature space to correct low-confidence or wrong transferred labels.



(a) Similarity graph examples (b) Distributions prior to propagation (c) Distributions after one step propagation

Note how the center node changed from blue to yellow
Question: batch update or online update? Ans: batch

Graph construction: each node is an observation from the dynamic sensor.

Neighborhood: edges connect k-nearest observations using a Gaussian similarity measure.

Refinement: label distributions are updated through neighbors, so similar instances converge toward similar labels.

Validation: Datasets and Methods

The authors evaluated whether SDVL generalizes across controlled and public wearable-sensor datasets.

IRH Dataset

Authors' collected data
9 subjects, 22 activities
5 Shimmer sensors
50 Hz, >28.5M samples

OPPORTUNITY

Public dataset
4 subjects in ADL (activities of daily living) scenarios
IMUs on back and arms
Locomotion labels: sit, stand, lie, walk

SDA Dataset

Public dataset
19 daily and sport activities
5 motion sensor nodes
25 Hz, >9.12M samples

Compared Methods

Naive: reuse teacher classifier.

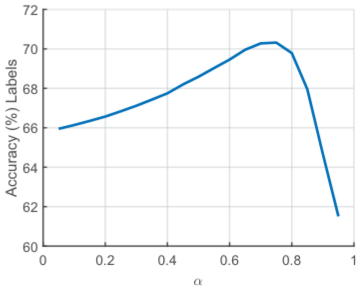
System-supervised: learner uses teacher-predicted labels.

Plug-n-Learn: calibrates labels, fixed learner location.

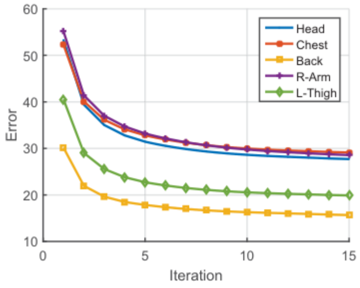
Upper bound: classifier trained with true dynamic-sensor labels.

Algorithm Design Choices

The paper tunes the label-propagation process and chooses the static classifier based on single-sensor accuracy.



(a) Accuracy vs. α



(b) Error (Energy) vs. # of iterations

Location	DT	kNN ($k = 3$)	SVM	Avg. (All Classifiers)
Head	63.2	45.5	73.3	60.7
Chest	61.0	45.8	66.5	57.8
Back	52.1	37.7	54.2	48.0
R-Arm	64.1	52.6	71.4	62.7
L-Thigh	57.4	37.9	58.8	51.4
Avg.	59.6	43.9	64.8	–

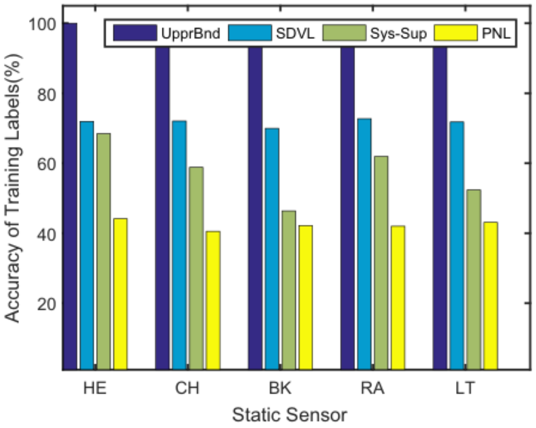
Mixing coefficient: α balances neighbor contribution against the original semi-label; the best observed value was around 0.75.

Stopping criteria: energy drops quickly in the first few iterations; the authors used about 5 iterations.

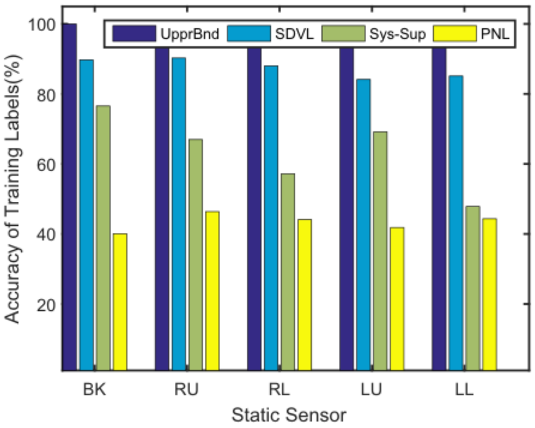
Static classifier: SVM produced the highest average single-sensor accuracy and was used for semi-label generation.

Results: More Accurate Automatic Labels

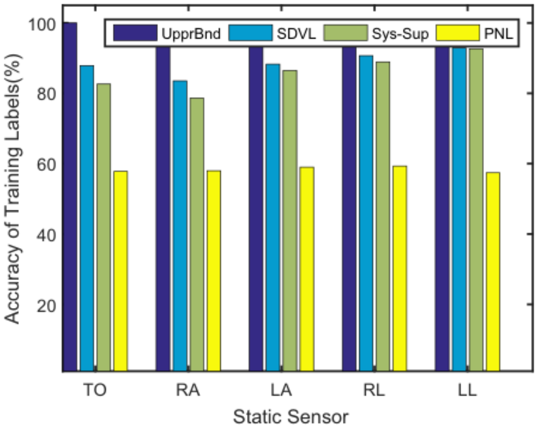
Before training the new classifier, SDVL first improves the quality of labels assigned to the dynamic sensor observations.



(a) IRH dataset



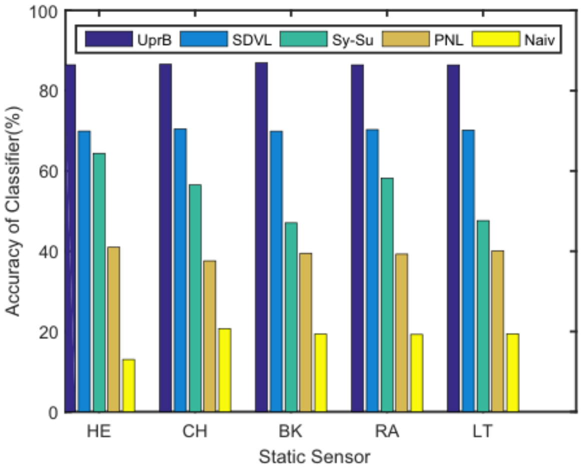
(b) OPP dataset



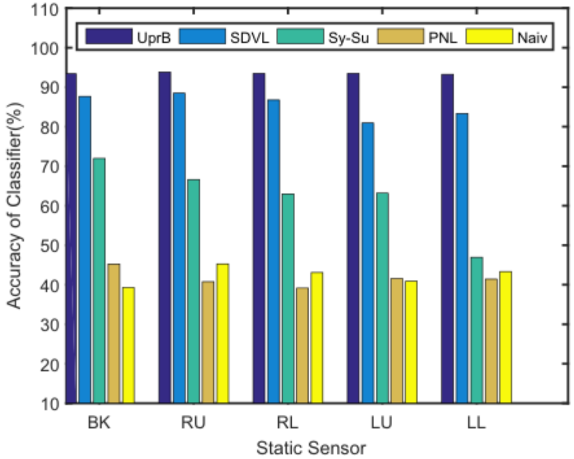
(c) SDA dataset

Results: Classifier Accuracy

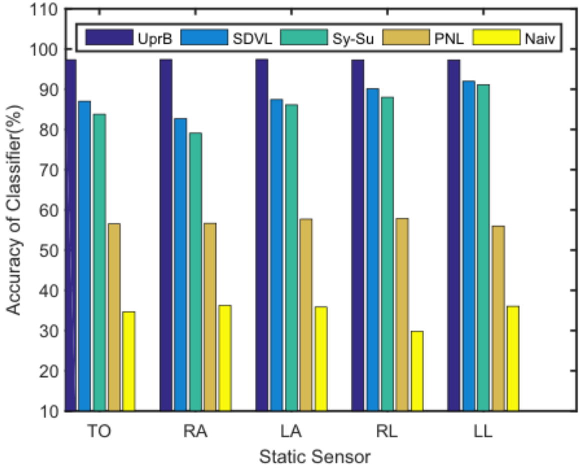
The refined labels were used to train an SVM classifier for the dynamic sensor.



(a) IRH dataset



(b) OPP dataset



(c) SDA dataset

Thank You!

Conclusion & Key Takeaways

Dynamic wearable systems need dynamic learning: one fixed training configuration is not enough for real-world use.

SDVL transfers knowledge without new labels: static sensors provide semi-labels while the dynamic sensor learns from synchronous observations.

Similarity-based refinement is the key step: label propagation helps revise weak teacher predictions using the dynamic sensor feature space.

Overall result: SDVL achieves strong accuracy gains and moves wearables closer to autonomous model reconfiguration.

Email: a.mamun@asu.edu

Paper

abdullah-mamun.com

𝕏: @AB9Mamun