Automated Walking Aid Detector Based on Indoor Video Recordings

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Introduction

Growth of elderly population
- Exponential growth in development of automated home care systems
- Due to rapidly growing elderly community → fall prevention neccesary
- Continuously monitor the gait speed and thus the fall risk of older people

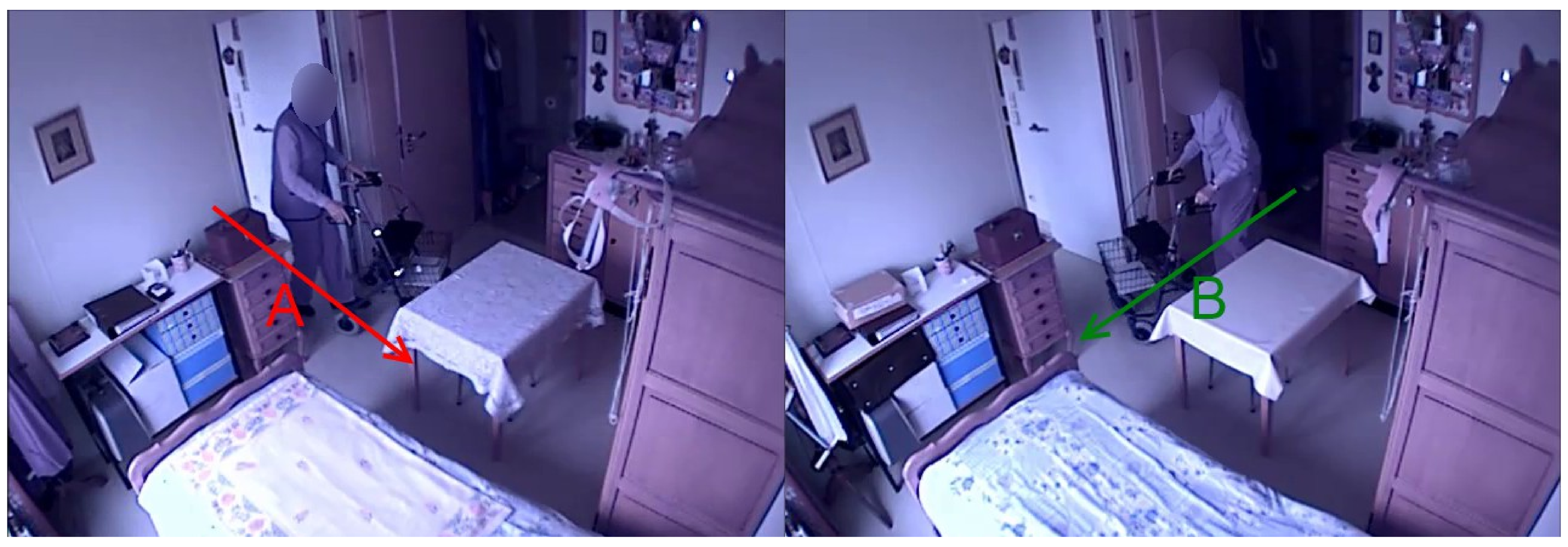
Automated detection of walking aids
- And more specific the case of a walker
- Automated detection of presence of walking aid in predefined trajectories
- Differentiate between walker and non-walker sequences automatically
- Measuring indoor usage of walking aids

Bringing together the healthcare and computer vision communities
- Using object detection techniques with a walker model
- Focus on classes with a large intra class variation
- Can lead to fully automated fall risk assesment

The setup

The acquired dataset

Dataset
- Multiple wall mounted IP cameras
- 75 year old living in a service flat (1 room monitored)
- Alternates between use of cane, walker and no walking aid at all

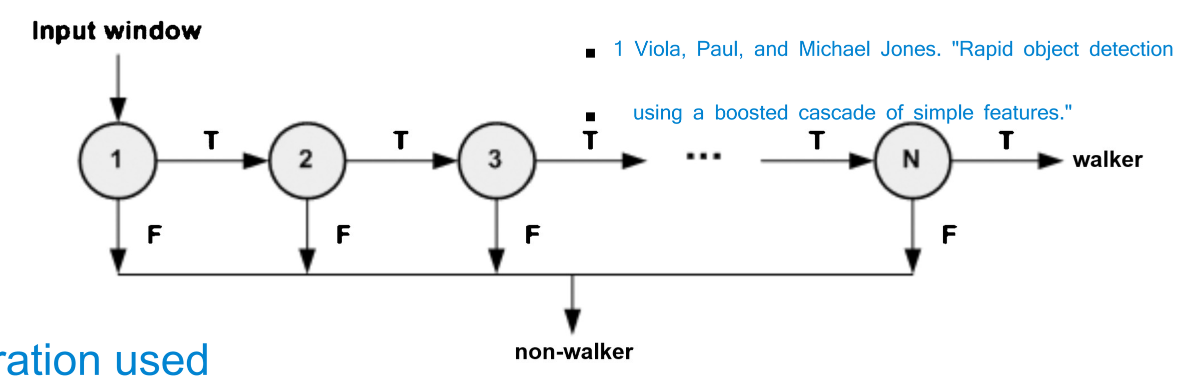


Selected data for training the walking aid models
- Two models for two preselected trajectories
  - → Model A = forward moving trajectory – forward movement, object side view
  - → Model B = reverse moving trajectory – reverse moving, object frontal view
  - → model NOT viewpoint invariant
- Walking aid sequences cropped from 444 pre-recorded walking sequences
- Each frame containing a visible walker was annotated to provide training data
- Both day and night conditions to increase model robustness to changing light

Some statistics about the amount of training samples used
- **Model A**: **(+)** 695 **(–)** 2000 / **Model B**: **(+)** 2200 **(–)** 4000
- Person can annotate about 500 objects/hour

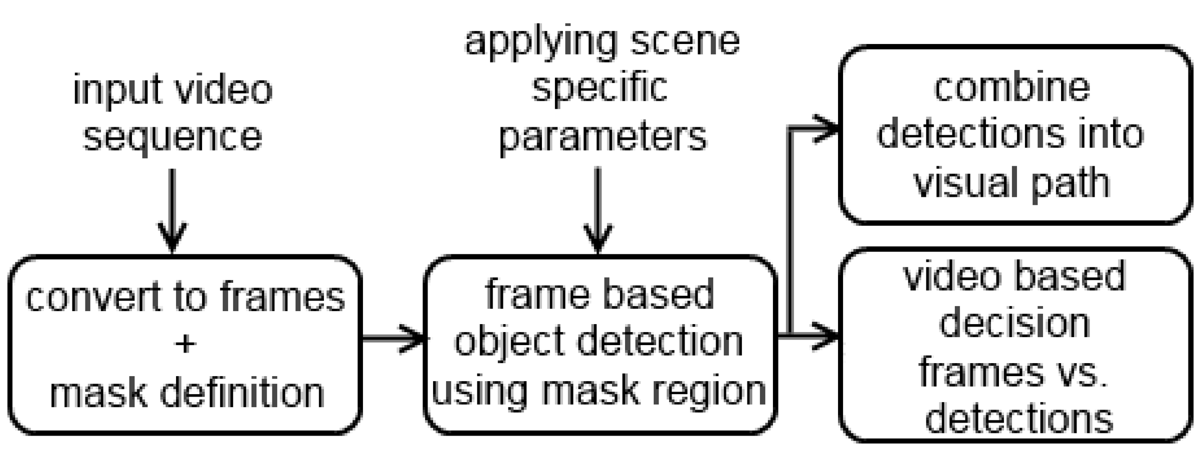
The object detection approach

OpenCV based Viola and Jones[1] framework for object detection
- Principle: strong classifier = cascade of weak classifiers
- Using AdaBoost machine learning on Local Binary Pattern features
- Trying to drastically reduce the amount of false positive detections
- Advantage of using early rejection principle



- 1 Viola, Paul, and Michael Jones. "Rapid object detection
- using a boosted cascade of simple features."

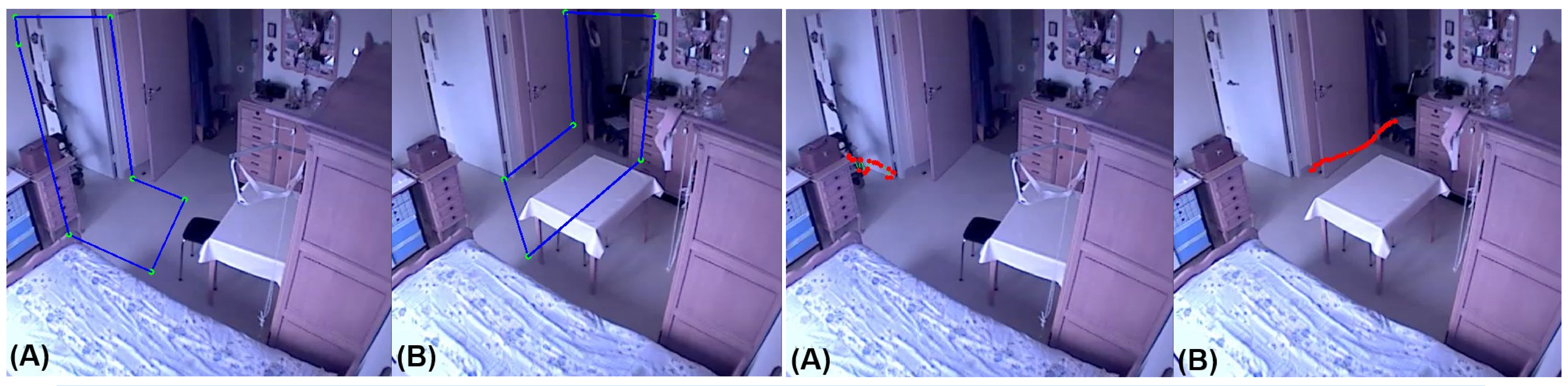
Configuration used
- Minimum hit rate 0,995 / maximum false alarm rate 0,5
- Correctly classify 99,5% of positive samples while classifying at least 50% of the used negative training samples correctly
- Both models < 4 hours of training



Complete pipeline

Using scene-specific information

Use knowledge of constrained scenery
- Define region of interest → desired trajectory measured = MASK
- Camera position known = average object size known for setup
  - Remove unnessary scale layers from evaluation
  - Reduce time to process a single image drastically
  - Less false positive detections in different scales → increase in accuracy



A frame-by-frame detection of object instances

Frame by frame detections still yield false positive detections
- Assume spatial relations between detections
- Visual storage of the result (see image above)
- D_R = reference detection previous frame, D_i = on of the current detections

$$D_R = \min_{i=1:N}[dist(D_i, D_R)]$$

Detection on a sequence base

Visual checking is too time consuming
- Instead of frame by frame basis → sequence based decision
- Is the walking aid used or not? → #D = number detections
- Depends heavily on the length of the sequence → #F = number frames
- Using a walker certainty score C_{walker}
- Optimal threshold by machine learning
  - Low enough to give sequences with low amount of detections a correct label
  - Based on 10 walker and 10 non-walker sequences → C_{walker} threshold = 0,2

$$C_{walker} = \frac{\#D}{\#F}$$

Results

Frame-by-frame versus sequence based

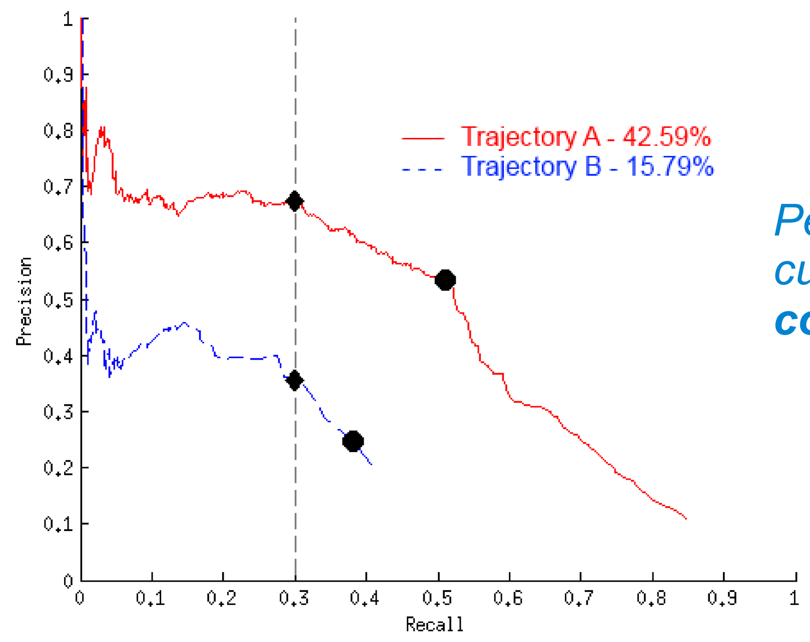


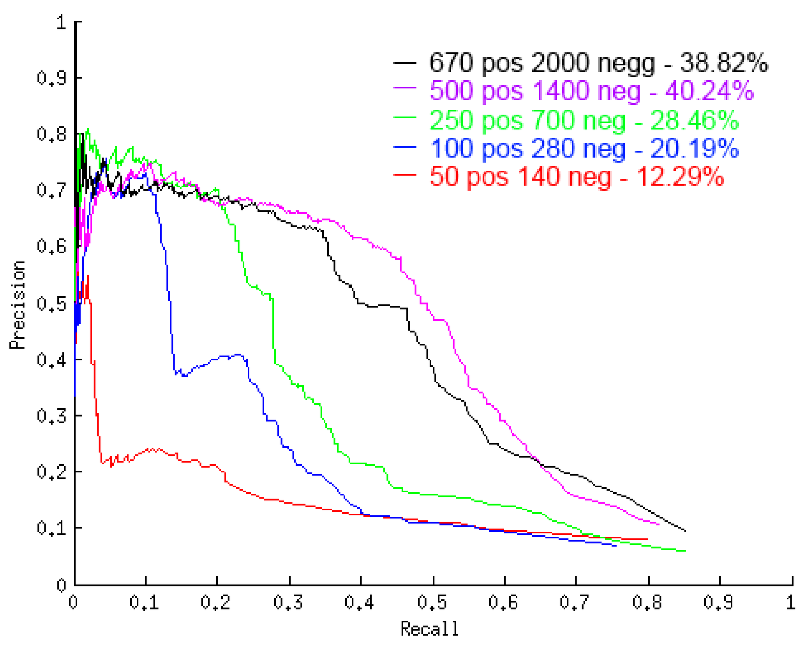
Fig. 6. Precision-recall curves for frame based object detection on both trajectory A and trajectory B. • denotes the best achieving configuration purely based on the model performance, while ♦ denotes the selected configuration for our specific setup.

*Performance measured by **precision recall** curves for frame-by-frame analysis and through **confusion tables** for sequence based analysis.*

Confusion matrix of algorithm output using both trajectories A and B with a $C_{walker} = 0.2$.

	Classified as Walker	Classified as Non-Walker
Walker Sequence	14	2
Cane Sequence	0	6
No Aid Sequence	0	4

Training data versus accuracy



Goal = as less manual input as possible
- Caregivers do not have days to train new models for new setups
- Trying to find an optimal amount of samples for a specific setup
- Heavily dependent on the situation

Future work
- Make sure that this relation is investigated deeper and further
- Automated decision on amount training data based on setup constraints

Conclusion

A successfully working and fully automated walking aid detection system
- Achieved a 92,3% accuracy on the testing data
- Could be expanded to other walking aids like canes

Respected time constraint → easy and fast to setup up using limited training data

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