GMM Classification for Fall Detection

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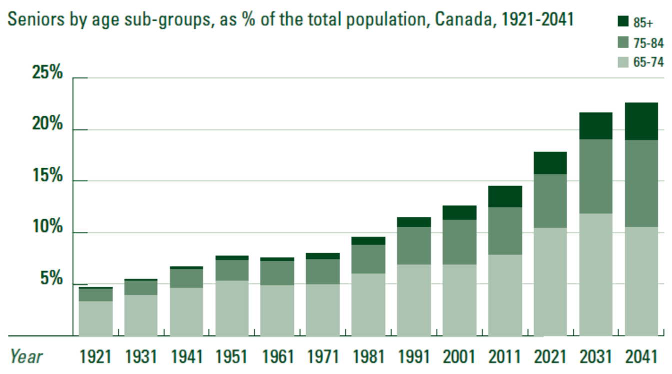
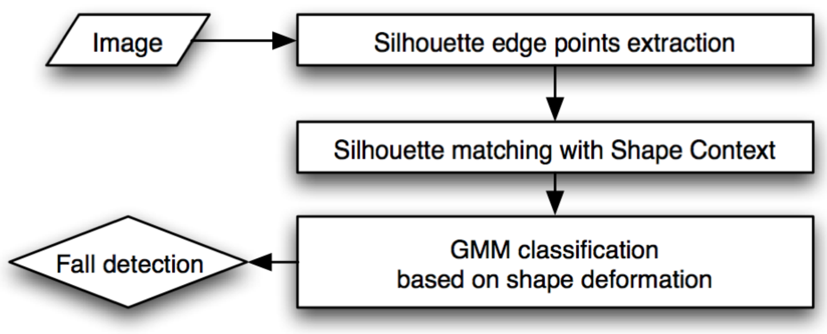
INTRODUCTION

- ***Context***
  - Growing population of seniors

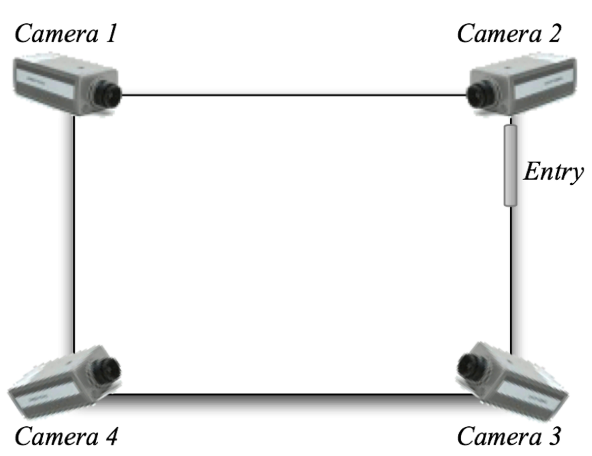


  - In 1996, 93% of seniors resided in private house. 29% of them lived alone [3].
  - Falls: one of the major risk for old people living alone.
- ***Usual solution:*** wearable fall detectors like accelerometers or help buttons. *Problem:* not worn properly, batteries needed, must be conscious after the fall
- ***Our solution:*** video surveillance system, entirely automated.
- ***Method:*** GMM classification of falls based on the human shape deformation.



DATASET

- **Four view points**



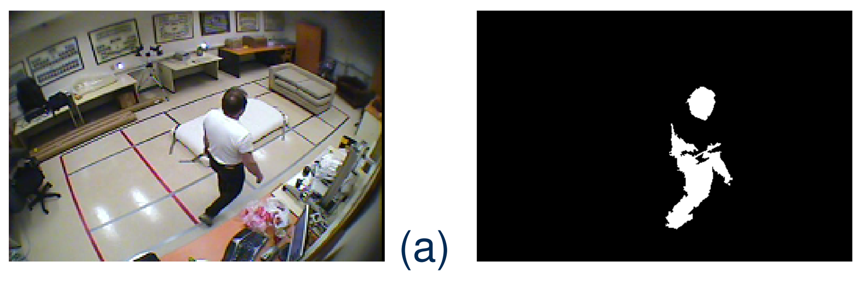
Camera 1 Camera 2

Camera 3 Camera 4

- **Daily normal activities** (22 lures like walking, sitting down, standing up, crouching down)
- **Simulated falls** (22 falls like forward/backward falls, falls when sitting down, loss of balance)
- **Realistic dataset** (difficulties like shadows, highlights, video compression, background clutter, occlusions, entering/leaving in the field of view, carried objects and differents clothes)

SILHOUETTE EDGE POINTS

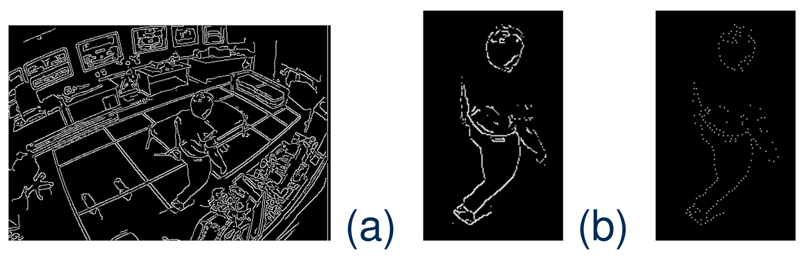
- **Foreground silhouette** obtained by background subtraction



(a) (b)

Fig. 1: (a) Original image and (b) foreground silhouette obtained. Due to compression, occlusions and bad segmentation, the silhouette is not clean enough to be used for shape analysis

- **Moving edge points**
  - Canny edges (better landmarks)
  - Moving edge points (Canny edge points combines to the foreground silhouette)



(a) (b) (c)

Fig. 2: (a) Canny edge detection, (b) moving edge points and (c) selected edge points ($N \approx 250$)

SHAPE CONTEXT MATCHING

- Shape descriptor: each point is encoded relative to its neighbours [1].
- Used here to match two human shapes.
- For each point p_i on the shape, we compute a log-polar histogram h_i of the relative coordinates of the remaining $n-1$ points:

$$h_i(k) = \#\{q \neq p_i : (q - p_i) \in bin(k)\}$$

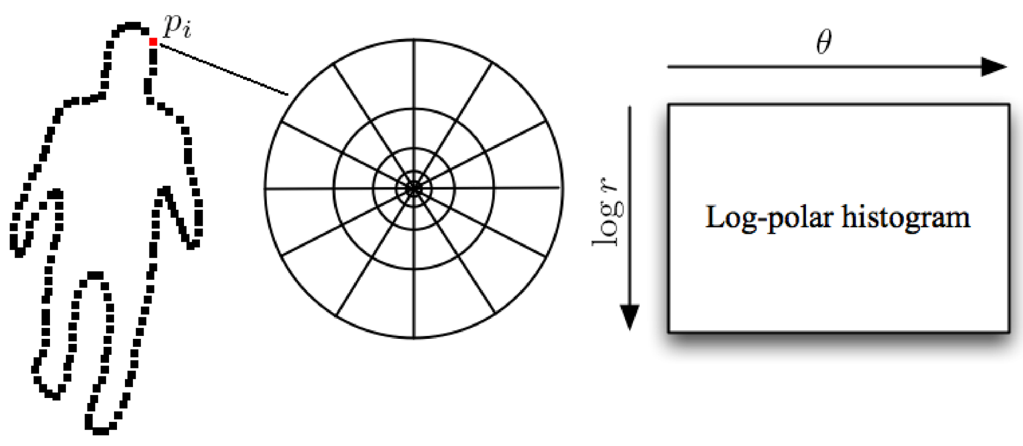


Fig. 3: Log-polar histogram computation for a point p_i. The log-polar histogram has 5 bins for $\log r$ and 12 bins for θ as proposed by the authors in [1].

- For each couple of points (p_i, q_j), a matching cost C_{ij} is computed with the χ^2 test statistic:

$$C_{ij} = C(p_i, q_j) = \frac{1}{2}\sum_{k=1}^{K} \frac{[h_i(k) - h_j(k)]^2}{h_i(k) + h_j(k)}$$

- We only keep the matching points which cost is minimal for the row and the column of the cost matrix (reliable landmarks)

PROCRUSTES SHAPE ANALYSIS

- The full Procrustes distance [2] between two centered complex configurations $y = (y_1, \cdots, y_k)$ and $w = (w_1, \cdots, w_k)$:

$$D_f(w, y) = \left\{1 - \frac{y^* w w^* y}{w^* w y^* y}\right\}^{1/2}$$

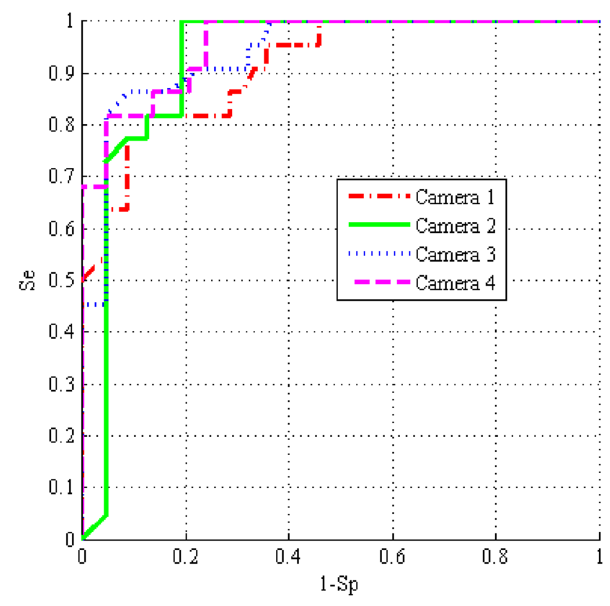
- D_f should increase in case of fall, and should be low after the fall

GMM CLASSIFICATION

- Gaussian Mixture Model (GMM) for outlier detection: one-class classifier trained with normal activities in the aim to detect abnormal events like falls
- Leave-One-Out Cross-Validation to train and test our dataset
- 2 features are used for classification:
  - D_{f_1}: the full Procrustes distance $D_f(t)$ at time t will be high in case of fall.
  - D_{f_2}: the mean value of D_f just after the fall, between $1s$ and $8s$ after the fall (to check a lying person).

EXPERIMENTAL RESULTS

- ROC curves for each camera independently (GMM with 3 components)



- Ensemble classifier with all cameras:
  - Majority vote (abnormal event if detected for at least 3 cameras)
  - $Se = 100\%$, $Sp = 95.5\%$ with threshold at 99.7% of normal data. All falls are detected and only one normal event is detected as a fall (when the person brutally sits down in the sofa)

CONCLUSION

- The edge matching is robust to occlusions, and gives really good results in spite of low-quality images and segmentation difficulties
- GMM classification with normal event: the 'fall class' is not required
- Robust method which can run in real time at 5 fps which is sufficient to detect a fall

ACKNOWLEDGMENT

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References

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