Sensor placement for activity recognition: comparing video data with motion sensor data

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***Abstract*—** The development of ubiquitous sensing strategies in home environments underpins the promise of adaptive architectural design, assistive robotics, and services which would support a person's ability to live independently as they age. In particular, the ability to infer the actions and behavioral patterns of an individual from sensor data is key to effective design of such components for *aging in place*. Frequently, activity recognition is accomplished using vision based sensors. The method employed in this paper makes use of self similarities in a video motion sequence to construct a descriptor of the activity in the form of a Histogram of Oriented Gradients (HOG). Descriptors are used as exemplars for classification and are shown to accurately identify motion video recorded from other views. Three candidate motions were performed using a PUMA robot (for repeatability). Video of each motion was recorded from an array of vantage points on the surface of a virtual sphere surrounding the workspace of the robot. This method is then extended to non-video motion sensor data collected from the same set of points. Results show that mean HOGs generated from Self Similarity Matrices may serve as effective exemplars to classify motions in both video and non-video formats. Video data provides superior classification results. However, motion sensor data offers a less intrusive option with promising accuracy especially when multiple sensors outputs are fused to form aggregate readings.

***Keywords*—** Activities of daily living, Activity recognition, Aging in place, Sensor placement, Self similarity

I. Introduction

A. Motivation

MObility decreases as we age. Such reduction, whether gradual or sudden, may ultimately impair one's ability to perform essential Activities of Daily Living (ADLs). Often, it is vital to ensure that older adults have the ability to perform ADLs independently [26]. For those wishing to age in place, a reduced capacity to conduct ADLs may be associated with diminished quality of life, decreased independence, the need for higher caregiver burden, or even institutionalization [6]. This paper discusses an innovative effort to sense and characterize user activity through active sensor placement. Successful application of these results could form the basis of a comprehensive system of adaptive robotic and architectural components to support independent living for individuals whose capabilities and needs are changing over potentially long periods of time.

The loss of dexterity in the hand is a key factor affecting performance of certain ADLs including precision and grip tasks. Further, decreased manual dexterity is often coupled with pathological conditions such as osteoporosis and Parkinson's disease, making this an interesting area of research [3]. For the current study a selection of representative tasks were examined: reaching (e.g., for a cup), grabbing (e.g., the bed rail) and pressing (e.g., a call button). These are all hand functions that have been used in studies exploring hand and finger mobility in aging adults [12],[21].

Architects and environmental designers attempt to accommodate those with reduced mobility through the use of Universal Design Principles (UDP) and smart home technologies. UDPs ensure that the environment does not confound an individual's efforts to complete tasks. UDPs make the environment safe, clean, legible and barrier-free [11],[14],[23] for all occupants, regardless of ability. These strategies facilitate resident mobility and independence. However, the majority of current implementations are static and of low fidelity, with accommodation solely the result of the form and placement of furniture and fixtures.

Smart homes extend awareness, increase control over systems, and enhance the security, healthfulness and safety of the environment through sensing, inference, communication technologies, decision-making algorithms and appliance control [5],[10],[13],[19]. These efforts are mostly focused on building systems because the real-time processing of occupant activity is expensive and often relies on technologies considered intrusive of people's privacy. As a result, most occupant sensing in smart homes remains low fidelity. Smart home technology would benefit greatly from the capacity to sense motion with high fidelity. In particular, this would facilitate development of robotic components to actively support user need while preserving privacy.

Such robotic components would allow for learned inference of user action and intention through persistent monitoring. Further, degradation in the abilities of the user could be tracked over time so as to adaptively inform the robot's assistive action plans. For example, a robotic bedside table might keep inventory of personal items, provide automated reminders, control lighting and music, or provide critical care alerts to medical personnel. With knowledge of typical user motion patterns the robot could respond to gestured commands or detect infrequent needs such as assistance with reach, weight transference, or ambulation.

A significant body of work exists in the area of automated recognition of human activities. Clearly, detection of user activity and inference of user context and intention are central to action planning by system software and robotic components. Despite the development of many promising techniques, the goal of robust activity recognition remains elusive. Due to such factors as changes in lighting and camera position, variations in anthropometry, and speed of execution, the problem remains largely unsolved [2],[16],[24].

Frequently, activity recognition research revolves around the use of visual images to analyze the behavior of human participants through tracking and kinematic analysis of physical geometry (limb dimensions, joint angles, etc.) [2]. However, it has been seen that many users find the presence of cameras to be intrusive in certain situations [1],[9]. Hence, this paper explores an non-structural approach previously applied to video surveillance for its applicability to non-vision based sensing. Also, the claim that the perception of human motion is invariant to changes in viewing angle [16],[24] is examined. The analysis discussed here first validates results from video data and then applies the same method to IR motion sensor data. These sensors were selected to allow for greater user privacy while also being insensitive to variations in lighting.

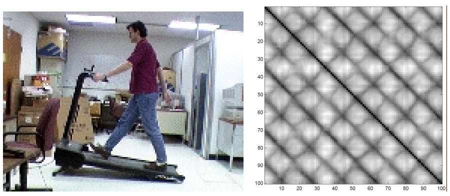
B. Related Work

Toward the determination of user activity context, two approaches have been widely used. Most broadly (on a household scale), observations and sensing of a user's interactions with the objects in their environment have been used to quantify discrete *events* such as entry or exit of rooms, appliance actuation, eating, drinking, toileting activities, etc. Such events are often sensed through the use of binary (switched) sensing devices [4],[25],[27] or wearable (accelerometer or RFID) sensors [20],[22].

Less broadly and of close application to the current study, the motions comprising actions themselves may be analyzed. Research in this area can be roughly divided into two main components. First, a representation of the motion in some compact form is computed. The representation is then subjected to a pattern classification technique so that it may be assigned to one of a known gallery of activities. Representations may be further broken down into feature-based (parametric) versus holistic (nonparametric) forms. Parametric representations extract features related to the physical geometry and kinematics of the actor. Classification may take advantage of known characteristics of motion to improve accuracy. Holistic representations utilize image statistics of the motion performed in (x, y, t) space. Hence, with regard to the frequently employed visual images of motion, these can also be characterized as pixel-based representations [2]. In this paper, a holistic representation is used. However, our analysis is performed with both visual and non-visual motion data.

Karahoca et al. [18] utilize Motion History Images (MHI) along with Hu moments to reduce the dimension of image sequence data while remaining scale and translation invariant. Histograms of Oriented Gradients (HOGs) are used in [8] to generate regional descriptors of still images for human detection. Using this technique, object appearance may be characterized by the distribution of image intensity gradients without specific information of where the gradients or image edges occur. For this method, an image is divided into *cells*. A normalized histogram of gradient directions for pixels in each cell is constructed. Concatenating the histograms over the collection of cells forms an image representation which may be used for classification. Gradients are computed using the Prewitt operator which has been seen to yield favorable results over other kernels. Smoothing was shown to decrease discriminative performance.

It has been shown that periodic motions such as walking or running may be recognizable solely from the movement of lighted feature points placed on the actor's body [15]. This phenomenon is exploited by Benabdelkader et al. [2], and Cutler and Davis [7] through the concept of self-similarity. In this approach, the locations of features in an image sequence are seen to generate a repeating pattern from which a motion descriptor may be generated. The set of features is tracked through the course of an image sequence. The summed distances of features between image pairs is computed. Performing this summation exhaustively across all image pairs forms a Self-Similarity Matrix (SSM). The main diagonal of the SSM is composed of zeros (since the entries represent image distances from themselves). Diagonals which are parallel to the main diagonal represent periodicity of motion, while diagonals which are perpendicular to the main diagonal represent symmetrical patterns in the observed motion (e.g. key body poses while walking) [7]. With the SSM, the periodic motion of a moving person is observable across image sequences as in Figure 1.



(a) (b)

Fig. 1. Walking action (a) and the associated SSM showing periodicity (b) [7].

In [16], motion descriptors are constructed from the HOG of the SSM. The authors argue that SSMs are approximately stable in appearance at varying camera angles (view invariant), and thus, their HOGs may be used as robust classifiers. The intuition of this approach centers around the idea that image features in a periodic sequence will attain a similar spatial orientation regardless of placement of the camera. The experimentation described in the following sections builds upon [28] and makes use of this approach to classify certain selected motions from video sequences. However, none of the approaches described above examines the possibility that the sensors need not be cameras. Hence, the key innovation in this paper is to also apply the above procedure to *motion sensor data* to assess whether classification remains viable.

II. Method

This section describes the laboratory fixture used to collect both video and motion sensor data as well as the analysis technique used to generate descriptors and classify motions. Data were collected for three activities which were chosen for their fundamental importance to a person lying in bed, as in a healthcare setting. These activities included:

1) (*Reach*) Bringing a cup to the mouth.
2) (*Press*) Pressing a nurse call button.
3) (*Grab*) Grabbing the bed rail.

A. Data Collection

Data sets were collected at 17 Hz over seven second intervals using both a camera and a Panasonic AMN23112 analog IR motion sensor. For repeatability, the motions were performed by a PUMA robot acting as a stand-in for the human arm. Sensor data were recorded from an array of points over the surface of a virtual sphere surrounding the workspace of the robot. A mock up of the scenario as it might exist a hospital environment is shown in Figure 2. Building on the work of [17], we envision a conformable sensor contour that would be capable of assuming an optimal vantage point geometry about the resident based upon learned patterns of activity.

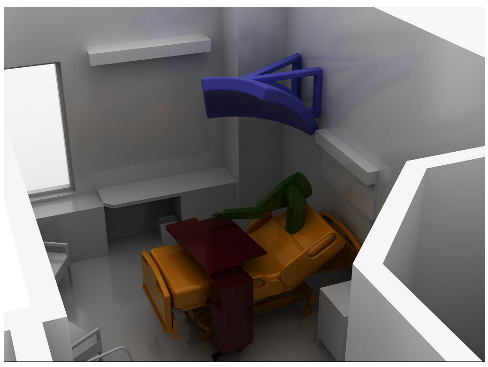


Fig. 2. Hospital room scenario with continuum sensor surface.

A rotating arc fixture was constructed to sweep the surface of the sphere in order to facilitate precise positioning of sensors (Figure 3).

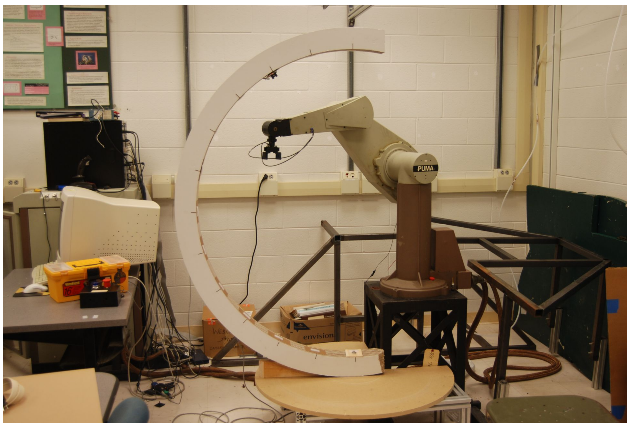


Fig. 3. PUMA robot with fixture for spherical sensor positioning.

Sensor vantage points (r, θ, ϕ) were selected such that $r = 30$", $\theta \in \{0°, 30°, 60°, \ldots, 180°\}$ and $\phi \in \{0°, 30°, 60°, \ldots, 240°\}$. For our purposes, the angle θ is measured downward from $0°$ at the vertical axis. This array of 63 points is depicted in Figure 4. In the descriptions which follow, images for video data are analogous to individual motion sensor readings with a sampling rate equal to the frame rate of the camera. This discussion holds for both data types.

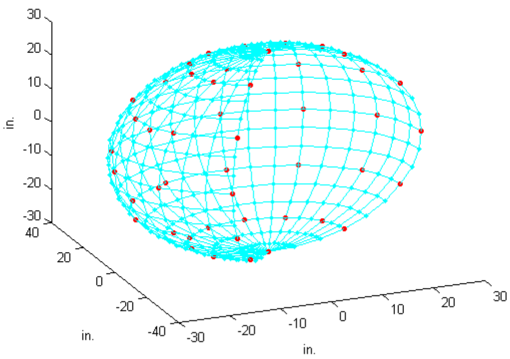


Fig. 4. Sensor vantage points at $30°$ increments.

B. Descriptor Calculation

The Self Similarity Matrix $S(I)$ for each image sequence $I = \{I_1, I_2, \ldots, I_N\}$ is calculated using (1)

$$S(I) = \begin{bmatrix} 0 & d_{12} & d_{13} & \ldots & d_{1N} \\ d_{21} & 0 & d_{23} & \ldots & d_{2N} \\ \vdots & \vdots & \vdots & & \vdots \\ d_{N1} & d_{N2} & d_{N3} & \ldots & 0 \end{bmatrix} \qquad (1)$$

where elements of $S(I)$ represent the Euclidean distance measure between image pairs in I such that

$$d_{i,j} = ||I_i - I_j||_2 \qquad (2)$$

Assumptions implicit in the distance calculation of (2) are that, for a given sequence, the sensor does not move and that the background does not change. Hence, any change in the intensity of a given image pixel denotes movement of a feature point. Thus, the total movement of all features can be represented as the difference between the image pairs.

A local (overlapping) HOG descriptor is calculated for each point $i = 1 \ldots N$ on the main diagonal of $S(I)$ where $N = 116$ for both video and motion data. The descriptor consists of a histogram of $m = 8$ gradient direction bins for each of $j = 11$ log-polar cells as shown in Figure 5. Gradients are computed using the Prewitt operator as suggested in [8]. Bin entries are weighted by the associated gradient magnitudes. Since $S(I)$ is symmetric, only the entries above the diagonal are included in the descriptor computation. Descriptors for all points are concatenated to form a composite descriptor H for the action sequence. Hence, for our data set, H is an $(8 \times 11) \times 116 = 8 \times 1276$ matrix.

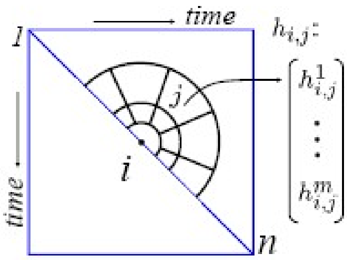


Fig. 5. HOG descriptor format [16].

C. Action Classification

Class exemplars for each of the three candidate actions were calculated as the mean HOGs for a specified percentage of the available data. These HOGs were selected randomly and constituted the training data. The remainder of the data points were used as test data. Each test data HOG was compared with each of the exemplars and classified by the exemplar to which it was nearest according to (3)

$$i = \arg\min_j D_E(H_{test}, H^j_{train}) \qquad (3)$$

where H_{test} is a test data point, H^j_{train} is one of $j = 3$ candidate action classes, D_E is the distance to the exemplar using the Frobenius norm, and i is the classification. The percentages of data points used as training data were varied from a single vantage point up to 50%, at 10% increments. In this way, it was possible to determine whether a descriptor from any given vantage point resembled that of its class exemplar so as to validate/invalidate the claim that the stability of the SSM allowed for robust view invariance.

TABLE I
VIDEO CLASSIFICATION RESULTS.

	Classification Accuracy (%)		
Training Points	Reach	Press	Grab
1	84.11	77.82	90.24
10%	95.70	90.96	100.00
20%	96.18	93.43	99.90
30%	96.00	93.11	100.00
40%	96.05	94.21	100.00
50%	96.41	92.50	100.00

III. EXPERIMENTAL RESULTS

The stability of SSM appearance for the video data set can be seen in Figure 6. The figure shows SSMs taken from orthogonal views for each motion class: $(r, \theta, \phi) = (30", 90°, 0°)$ for column 1, $(30", 90°, 90°)$ for column 2, and $(30", 180°, 0°)$ for column 3.

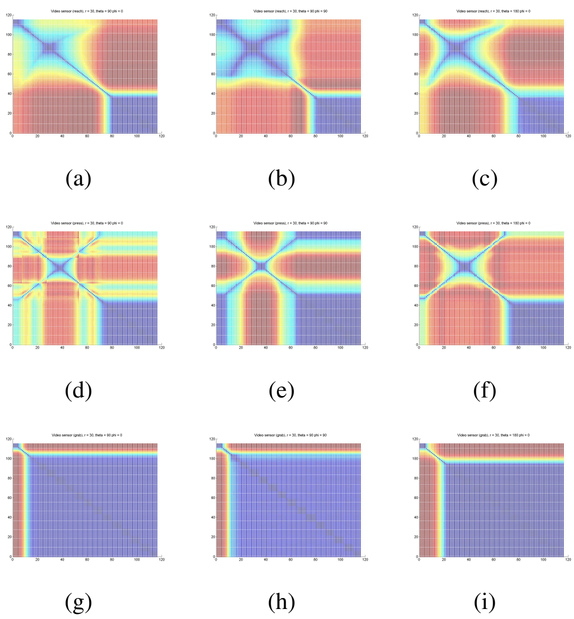


Fig. 6. SSMs for video sequences taken from orthogonal views: reach (a,b,c), press (d,e,f) and grab (g,h,i).

A. Video Data Classification

Classification results for the video sequences are given by Table I. Because exemplars were calculated using a percentage of the available data points selected at random, any individual execution of the classifier could be expected to yield wide ranging results. To mitigate this effect, all statistics shown in the table have been averaged over twenty classification runs. Results were very favorable ($>$ 90% accuracy) when multiple data points (10% and higher) were used to calculate the exemplars. Further, they show continued improvement as more data points are used to compute exemplars. It is notable that, when a single data point was used as a class exemplar, over 77% classification accuracy was still achieved. This result lends credibility to the assertion by [16] that the stability of SSMs is independent of vantage point and that the method does support view invariant activity recognition. Also, since the *grab* motion is kinematically distinct from either *reach* or *press*, classification accuracy is generally highest for this class.

B. Motion Sensor Data Classification

SSMs for motion sensor data readings taken from the vantage points used above are given in Figure 7. It can be seen that, although there is a nominal resemblance between SSMs for a given class, the similarity is clearly less than that for video SSMs.

Classification results for the motion sensor readings are given by Table II. Results are poor when only a single view is used to generate exemplars - no better than random guess. Again, the *grab* motion shows greatest accuracy, owing to its inherent dissimilarity from the other motion classes. Results improve as the percentage of data used to train the classifier is increased (reaching 65% - 70%), though, not to a level that can be considered reliable.

Clearly, motion sensor data does not carry the richness of information found in video data. However, results with motion sensor data are promising. To increase the amount of information available for activity classification through motion sensing, two approaches are attempted. First, as suggested in [27] increasing the number of sensors offers an

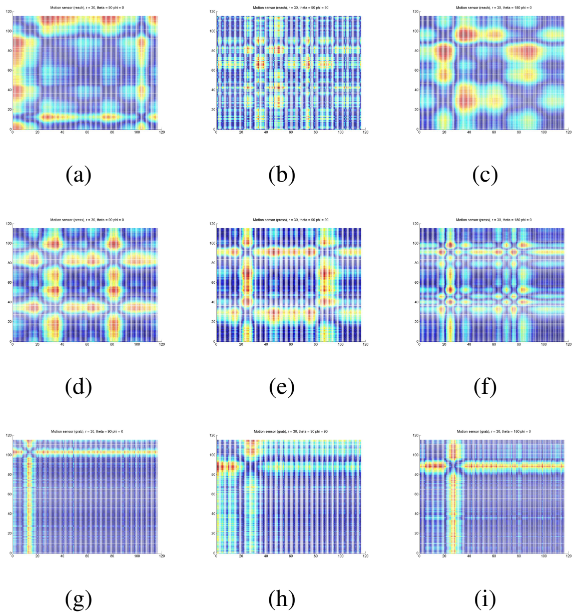


Fig. 7. SSMs for motion sensor input taken from orthogonal views: reach (a,b,c), press (d,e,f) and grab (g,h,i).

TABLE II

MOTION SENSOR CLASSIFICATION RESULTS.

Training Points	Classification Accuracy (%) Reach	Press	Grab
1	25.08	24.68	86.45
10%	50.79	56.32	88.60
20%	56.27	63.04	93.73
30%	61.89	61.78	94.78
40%	60.39	73.68	96.97
50%	65.63	70.16	96.56

TABLE III

MOTION SENSOR CLASSIFICATION RESULTS FOR SENSORS AT $15°$ INCREMENTS.

Training Points	Classification Accuracy (%) Reach	Press	Grab
1	37.50	35.82	88.60
10%	65.73	65.90	97.16
20%	72.39	73.30	98.99
30%	75.00	75.40	98.84
40%	75.04	74.18	99.08
50%	74.87	76.37	98.93

TABLE IV

MOTION SENSOR ARRAY CLASSIFICATION RESULTS.

Array Size	Classification Accuracy (%) Reach	Press	Grab
1×1	56.27	63.04	93.73
1×2	76.18	75.78	98.63
2×2	86.76	86.18	100.00
3×3	94.90	95.39	100.00

intuitive method for increasing available information. To this end, the density of vantage points for motion sensing was increased to $15°$ increments over the sphere such that points (r, θ, ϕ) were $r = 30$", $\theta \in \{0°, 15°, 30°, \ldots, 180°\}$ and $\phi \in \{0°, 15°, 30°, \ldots, 255°\}$. This constellation of sensors effectively quadruples the original motion sensor data set to 234 points. Classification accuracy for this scenario improved by, typically, 5%-15% as can be seen in Table III. Still, however, such results do not practically approach the results available through video sensing.

Second, a surface contour encompassing an array of sensor vantage points is envisioned. Such a contour may be emulated by fusing sensor inputs by averaging readings over regional subsets of the virtual sphere. Table IV shows several scenarios for such arrays. The table assumes 20% of data points were used to calculate class exemplars. Using this scheme, motion sensor data approaches the accuracy found using video data for arrays of 2×2 and larger.

IV. CONCLUSIONS AND FUTURE WORK

In this paper, the use of SSMs to generate HOG classifiers for activity recognition has been explored. It has been shown that video recordings of basic motions can be classified by this method with a high degree of accuracy.

Further, and most interestingly, we have used *non-video* motion data to evaluate whether a holistic activity model might be useful in privacy sensitive applications. It has been shown that motion sensor readings of basic actions can be classified by this method with a promising accuracy. Where single sensor inputs are used as class exemplars, classification accuracy is poor and highly sensitive to vantage point. Where multiple descriptors are averaged to produce exemplars, classification improves but is still subject to the choice of vantage point for best outcomes. Coupled with our robust classification for video, we interpret these findings as supportive of sensor view invariance in that the *appearance* of SSMs for a given class is stable enough over the range of vantage points to collectively form a useful discriminant.

Experimentation with single motion sensor inputs (test data) also yielded poor results. However, when multiple sensor views are combined into a single average reading for a small contour surrounding a vantage point, results improve significantly. Hence, the use of motion sensor data for the purpose of activity recognition appears to be a viable area for continued exploration. Future work is foreseen in the addition of new motion classes with more complex kinematics and the use of HOGs to predict optimal vantage points for hard-to-recognize action classes.

Because the classification technique used computes a distance to a mean HOG exemplar, the vantage point whose distance to the exemplar is shortest can be considered the optimal vantage point for a given action. The prospect of an optimal vantage point gives rise to the notion that relocation of sensors to an optimal view might yield improved classification. Since human motions begin and end at arbitrary times and at varying speeds, we hypothesize a moving temporal *window* of action which might need to be sensed and classified continuously. Consequently, the problem formulation for our ongoing work in this area is to determine active sensor positioning which best captures an unfolding scene in the course of everyday life.

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