Estimating Daily Energy Expenditure from Video for Assistive Monitoring

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ABSTRACT
Automatically estimating a person's energy expenditure has numerous uses, including ensuring sufficient daily activity by an elderly live-alone person, such activity shown to have numerous benefits. Most previous work requires a person to wear a sensor device. We introduce a video-based activity level estimation technique to take advantage of increasingly-common in-home camera systems. We consider several features of a motion bounding rectangle for such estimation, including changes in height and width, and vertical and horizontal velocities and accelerations. Experiments involved 36 recordings of normal household activity, such as reading while seated, sweeping, and light exercising, involving 4 different actors. Results show, somewhat surprisingly, that the feature horizontal acceleration leads to an activity level estimation fidelity of 0.994 correlation with a commercial BodyBugg body-worn energy measurement device. Furthermore, the approach yielded 90.9% average accuracy of energy expenditure.

Categories and Subject Descriptors
J.3 [**Computer Applications**] - *health*.

General Terms
Algorithms, Measurement, Reliability, Experimentation.

Keywords
Assistive monitoring, smart homes, video processing, telehealth, energy expenditure, embedded systems, ubiquitous systems.

1. Introduction
Automatically estimating a person's daily energy expenditure has numerous uses, including determining whether an elderly person living alone is achieving sufficient levels of daily activity. The U.S. Centers for Disease Control and Prevention and various researchers suggest moderately-intense physically activity for at least 15 minutes, 3 or more times a week [6][18][19][25][28][29]. Expending energy through physical activity is associated with lower risks of mortality in older adults [12][21][28]. Studies show significant correlation between regular physical activity and delayed onset of dementia [5][18][19][37]. Sufficient physical activity reduces likelihood of falls [20], a leading cause of accidental death among persons over 65 [32]. Sufficient activity also positively impacts emotional well-being [11][26]. Automatic estimation of a person's daily energy expenditure can motivate a person to be more active [10], can assist family caregivers and clinicians to detect trends, make appropriate interventions to prevent serious problems, and ascertain adherence to regimens.

Figure 1 shows the daily energy expenditure dashboard of a person for 5 days. The last three days are comparatively low activity days. A caregiver could look at the dashboard and decide whether the three low activity days indicate a problem requiring intervention.

Most previous automatic energy expenditure estimation approaches require use of body-worn devices [3][4][35][40]. Body-worn devices have advantages relating to their accuracy and to their measurement of activity inside or outside the home. However, such devices have some key drawbacks, including that people commonly fail to wear the device (either intentionally or unintentionally) [2]. Meanwhile, cameras, often with privacy mechanisms that limit viewing or that distort images, are increasingly being installed in homes for assistive monitoring purposes, such as to provide security, detect falls, or classify activities. Cameras, along with other non-worn sensors such as floors with embedded sensors, can thus supplement or sometimes replace body-worn sensors for assistive monitoring purposes.

This paper introduces techniques for estimating a person's daily energy expenditure from video, comparing with a body-worn device.

Figure 1: Daily energy expenditure dashboard for 5 days. The graphs show the activity level across each day. The pie chart shows the activity level ratios for each day. The last three days have been low activity days, indicating intervention may be required. This dashboard view is intended to provide a simple method for quickly seeing activity level, achieved by quantizing into three levels. More levels could be used if more accuracy is desired

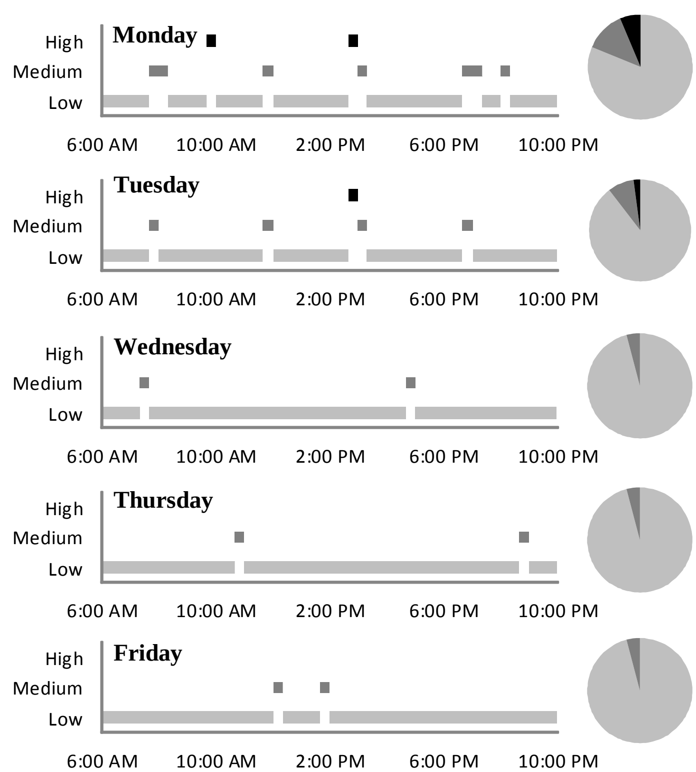
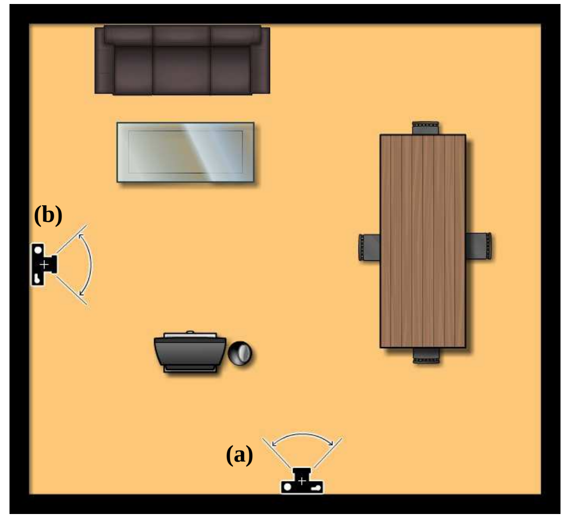


Figure 2: In-home environment included a living and dining room. The environment had 2 cameras. These pictures were taken from the (a) main camera and (b) supplementary camera.

(a) (b)

Figure 3: Floor plan of the in-home environment including the position and direction of the (a) main camera and (b) supplementary camera. (Floor plan created with http://floorplanner.com**)**



2. Background and related work

Daily energy expenditure can be directly calculated with a respiratory chamber that measures the oxygen consumption and carbon dioxide emission of a person [30]. Room-sized respiratory chambers cost about $1 million and are generally only used for specialized research purposes. Doubly labeled water (DLW) is the most tested and reliable *indirect* energy expenditure estimation method [33]. Commercially-available mobile body-worn DLW devices cost about $30,000 [8] and are primarily used for athletic performance optimizations. These daily energy expenditure options are too expensive for in-home use.

A common approach to estimating daily energy expenditure through energy expenditure is to wear a device around the upper arm, such as the BodyBugg [4] or Body Media's armband [3]. These devices cost about $150-$200 and estimate energy expenditure using algorithms operating on data from the device’s multiple sensors, which include a tri-axial accelerometer, a heat flux sensor, a galvanic skin response sensor, and a skin temperature sensor. The BodyBugg was compared to DLW for energy expenditure estimation and had on average 90% accuracy [15]. Our work uses the second (assumedly more accurate) version of the BodyBugg. Another common approach to estimating energy expenditure is to wear a pedometer, which counts the number of steps taken. While costing only a few dollars, pedometers are far less accurate for measuring energy expenditure [9].

Researchers have estimated daily energy expenditure with body-worn tri-axial accelerometers for nearly 30 years [24][35][40]. Zhang [40] built a system that used 5 tri-axial accelerometers: one on the chest, one on the frontal part of each thigh, and one on each foot. The system had on average more than 95% accuracy for estimating energy expenditure compared to a respiratory chamber.

Yao [39] used a body-worn camera attached to the user's shirt on the chest just below the neck, to distinguish between walking and jogging by measuring frame displacements, i.e., shifts in the video content. The frame displacements are periodic, and a single frame displacement period is analogous to a single stride. The average number of strides per second was 2.15 for walking and 2.9 for jogging. This method has not been compared to other activity level estimation methods.

Estimated daily energy expenditure could be inferred from activity recognition systems using well-established activity-to-energy-expenditure conversion charts, such as charts made by the Mayo Clinic [23] and other researchers [1]. Activity recognition systems have been developed using body-worn sensors [7][22], and off-body worn sensors [36][38] and cameras [13][31][41]. Choudhury [7] classified exercise activities using a watch-sized device that included a microphone, light sensor, 3-axis accelerometer, barometer, infrared sensor, humidity and temperature sensor, and a compass. Tapia [36] classified activities of daily living (ADL), such as preparing lunch and watching TV, using on average 80 contact switches and motion sensors in a single bedroom apartment. During the training phase, sensor activation routines were identified and correlated to activity labels. During the testing phase, these correlations were used to classify observed sensor activation routines as activities. Zhou [41] classified ADLs from video with a three level decision tree. The first level determines the general action, such as at the dining table or preparing a meal, by estimating the location and speed of the moving objects, assumed to be a person. The second level determines a more detailed action, such as eating or just sitting still at the dining table, from the amount of motion in the video. The third level determines the particular action for high motion activities, such as cooking or talking on the phone while in the kitchen, from the vectors motion. Ribeiro [31] describes a feature selection and classification architecture for activity recognition from video, using 29 features.

Our goal was to create a much simpler method that can estimate daily energy expenditure *without* first requiring activity recognition, as such a method may provide greater flexibility with respect to camera positioning and video quality requirements, may operate on privacy-enhanced video (e.g., blurred video), and may be implementable on lightweight processing resources (e.g., within a camera itself).

3. Recordings

We recorded 4 actors for 9 activities each in a mock in-home environment that included a living room and dining room, shown in Figure 2. The environment was located in a research laboratory at the University of California at Riverside. Each recording contained a single actor performing a single activity, such as reading while seated, wiping down surfaces, or using a stair stepper exercise machine. Each recording had a length of 30 minutes. For each recording, video from 2 cameras, the main camera and supplementary camera, was recorded at 30 frames per second, along with the BodyBugg energy estimates. A requirement for each recording was that the actor never left the main camera, shown in Figure 3(a).

Figure 4: Foregrounding via foreground-background segmentation takes as input (a) a background image and (b) a video frame, and outputs (c) a foreground. (d) A minimum bounding rectangle (MBR) is fit around the foreground.

We grouped the 9 activities into 3 categories based on the number of Calories[1] expended per minute according to the BodyBugg: low activity level (less than 3 Cal./min.), medium activity level (between 3 and 6 Cal./min.), and high activity level (more than 6 Cal./min.). The grouped activities are shown in Table 1.

The cameras came from a popular in-home 8-camera monitoring set made by Q-See and sold by Costco for around $400. The cameras were positioned and had viewing directions as shown in Figure 3. The cameras were 182cm above the floor.

4 male actors performed the various activities. Actor 1 was 18 years old, actor 2 was 21, actor 3 was 20, and actor 4 was 21.

4. Estimating daily energy expenditure from one camera

Our method for estimating activity level from one camera included three steps: foregrounding to extract the moving object, fitting a minimum bounding rectangle (MBR) around the moving object, and using a feature of the MBR to estimate activity level.

4.1 Foregrounding via foreground-background segmentation

Foreground-background segmentation extracts a moving object in the foreground from a static background. A typical moving object in a home is a person, particularly in the home of a live-alone elderly person. Foreground-background segmentation is a common problem in computer vision and many algorithms exist [17][16][34]. These algorithms typically learn non-changing parts of the video as a background image. The background image is subtracted from a video frame, resulting in only the moving objects.

We used the algorithm developed by KaewTraKulPong [16] and implemented in the OpenCV 2.2.0 library as the class BackgroundSubtractorMOG2. The algorithm outputs a foreground image in which white pixels are not foreground and black pixels are foreground. The black pixels were put into groups of adjacent pixels. If the largest group did not have an area of 100 pixels, then we abandoned the MBR fitting for this frame. These groups were sorted by size from largest to smallest. Groups that had a size smaller than 36 were eliminated. We assumed the largest group of black pixels was part of the person, thus the largest group became the person group. The increasingly smaller groups were merged with the person group if the smaller group was not more than 75 pixels away from the person group. When all groups had been considered, an MBR was fit around the person group. The algorithm output a foreground image (Figure 4(c)) and the MBR (Figure 4(d)).

We used two techniques to mitigate motionless actors from being learned by the background image: stop learning after 2 seconds of no motion and learning an additional image in which the previous frame's MBR area is replaced by the background image.

We used three filters to mitigate erratic changes in the MBR between consecutive frames: dampen, smooth, and glitch. The dampen filter set a maximum distance an MBR could move from the previous MBR with 24 pixels horizontally and 12 pixels vertically when both the current and previous MBR existed. When the current MBR existed but the previous MBR did not, the current MBR was limited to being within 10 pixels of the side of the frame. When the previous MBR existed and was not within 10 pixels of the side of the frame and the current MBR did not exist, the current MBR was created and copied the previous MBR location, height, and width. The smooth filter averaged an MBR location, height, and width with the previous MBR, unless the previous MBR did not exist. The glitch filter eliminated an MBR if 40 of the next 45 MBRs did not exist. Similarly, the glitch filter created an MBR using the same position, height, and width of the last existing MBR if 40 of the next 45 MBRs did exist and an MBR did not already exist.

Table 1: Nine activities were recorded and categorized as either low activity level, medium activity level, or high activity level.

Activity description	Activity level
Read a book while sitting on the couch	Low
Use laptop while sitting at dinner table	Low
Eat a meal while sitting at the dinner table	Low
Pace slowly in circles	Medium
Wipe the surfaces	Medium
Sweep the floors	High
Pace moderately in circles	High
Use stair stepper	High
Pace quickly in circles	High

4.2 Activity level estimation from the MBR

We considered eleven features of the MBR from which energy might be estimated: MBR height, width, vertical velocity, horizontal velocity, combined velocities (speed), vertical acceleration, horizontal acceleration, combined accelerations (change in speed), mechanical work, horizontal mechanical work, and vertical mechanical work. We also considered the amount of motion, which we define as the number of pixels that changed by more than a magnitude of 50 on the RGB scale. For each feature, we standardized the feature's data for each frame across a recording that has n frames, and then summed the absolute difference between each frame's feature data S_i and the previous frame's feature data S_{i-1}, as shown below:

$$\sum_{i=2}^{n} | S_i - S_{i-1} |$$

[1] Using the U.S. convention of 1 Calorie = 1 kcal or 4184 Joules.

Table 2: Correlations between eleven features based on the MBR and the motion in the video, and the BodyBugg energy expenditure estimation.

Feature of Bounding Box	Correlation with BodyBugg	p-value
Sum of height changes	r = 0.45	p < 0.01
Sum of width changes	r = 0.72	p < 0.01
Sum of vertical velocities	r = 0.72	p < 0.01
Sum of horizontal velocities	r = 0.77	p < 0.01
Sum of combined velocities	r = 0.77	p < 0.01
Sum of vertical accelerations	r = 0.70	p < 0.01
Sum of horizontal accelerations	**r = 0.80**	**p < 0.01**
Sum of combined accelerations	r = 0.79	p < 0.01
Sum of work	r = -0.22	p = 0.91
Sum of horizontal work	r = -0.16	p = 0.84
Sum of vertical work	r = -0.23	p = 0.92
Sum of motion in video	r = -0.01	p = 0.53

The features are standardized to minimize the invariance caused from the actor's distance to the camera. We take the absolute difference between consecutive samplings of a feature to determine the change in the feature. The absolute differences are then summed because energy expenditure accrues over time. The sampling rate was 30 times per second (i.e., 30 video frames per second).

We sought to determine which of the twelve features might best predict energy expenditure by comparing each feature to the BodyBugg energy estimation. The recordings by the four actors introduced in Section 3 were used. For each recording, the background image was trained for at least 10 seconds with no actor on scene before starting the foregrounding and MBR fitting. Figure 5 graphically illustrates the correspondence between one of the features, namely the sum of horizontal accelerations, and the BodyBugg energy expenditure estimation. A clear trend is that as the sum of horizontal accelerations increases, so does the BodyBugg estimate. Figure 6 illustrates the correspondence for the sum of combined accelerations, showing that the trend is comparable. The other 5 features shared comparable correlations, except for the sum of height changes, which had a much lower correlations and thus a weaker graphical trend.

More specifically, we examined correlations between each feature and the BodyBugg's energy estimate across the 36 recordings described in Section 3. The results are shown in Table 2. The sum of horizontal accelerations has a very strong correlation with the BodyBugg energy expenditure estimation, with r = 0.80 and $p < 0.001$. This result is not surprising as many in-home activities involve walking around the home.

To convert a horizontal acceleration to an energy expenditure estimate, we considered four regression models: linear, exponential, power, and logarithmic. The R^2 for each regression is as follows: linear had 0.6418, exponential had 0.6905, logarithmic had 0.6729, and power had 0.7577. Figure 5 shows the best fit power model for the sum of combined accelerations. Although power regression had the largest R^2 value, the other regression models had competitive R^2 values. Therefore, we considered all four regression models during the training phase of the experiments, and chose the best for each training set.

Figure 5: The sum of horizontal accelerations versus the BodyBugg energy expenditure estimates shows a strong correlation. Each point is a different recording.

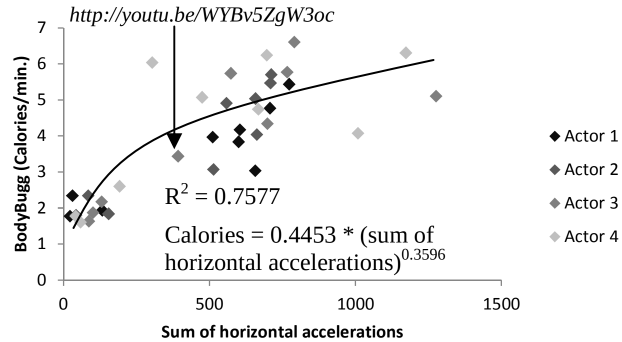
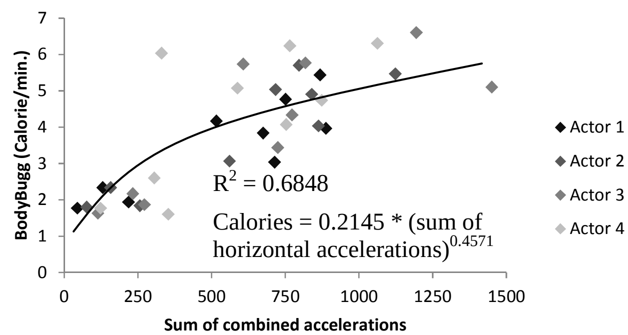


Figure 6: The sum of combined accelerations versus the BodyBugg energy expenditure estimate showed a the second strongest correlation.



5. Experiments to determine the fidelity and accuracy of one camera daily energy expenditure estimation

A key expected use of video-based activity level estimation is to compare a person's activity levels across many days, to detect negative trends and thus introduce interventions. As such, a goal of estimation is not necessarily accurate calorie estimation, but rather correct relative estimation of energy expenditure across days, including correct ratios among low/medium/high activity days. Thus, our first experiments sought to determine the *fidelity* of our video-based activity level estimation. We define fidelity as the correlation between the video-based energy estimation and the BodyBugg energy estimation (such a definition tolerates an offset between estimated and actual calories). The ideal fidelity is a correlation of 1.0.

We conducted experiments to determine the fidelity of our video-based activity level estimation based on sum of horizontal accelerations, compared to BodyBugg estimates, for three different 16-hour constructed days per actor. Fidelity is the per-actor correlation between video-based energy estimation and the BodyBugg energy estimation.

We considered three different types of days per actor: low activity day, medium activity day, and high activity day. A low activity day was defined as 920 minutes at low activity level and 40 minutes at medium activity level. A medium activity day was defined as 860 minutes at low activity level, 80 minutes at medium activity level, and 20 minutes at high activity level. A high activity day was defined as 780 minutes at low activity level, 120 minutes at medium activity level, and 60 minutes at high activity level.

Recording three full 16-hour days of activity for each actor was not practical for our actors. Instead, we recorded a variety of shorter segments for each actor, yielding the 36 videos discussed earlier. Then, we constructed 16-hour days for each actor by composing various segments of the actor into a realistic day. Figure 7 shows some of the activities that made up the constructed day for actor 1. We trained a regression model using the nine recordings from each of the other 4 actors, i.e., using 36 training videos. We considered four regression models for the training: linear, exponential, logarithmic, and power regressions. The regression model with the largest R^2 value was selected and used to test the low, medium, and high days for actor 1.

The same process of constructing days, training and choosing, regression models, and testing constructed days was repeated for each actor.

The measures considered for the evaluation of a daily Calorie estimate are:

- Fidelity - The fidelity per actor is the correlation (r-value) between the BodyBugg estimate and video-based estimate of Calories expended for an actor. An r-value of 1.0 is the ideal.
- Accuracy - The accuracy is 1 minus the approximation error, which is the absolute difference between the expected value and the observed value divided by the expected value. Accuracy of 100% is ideal.

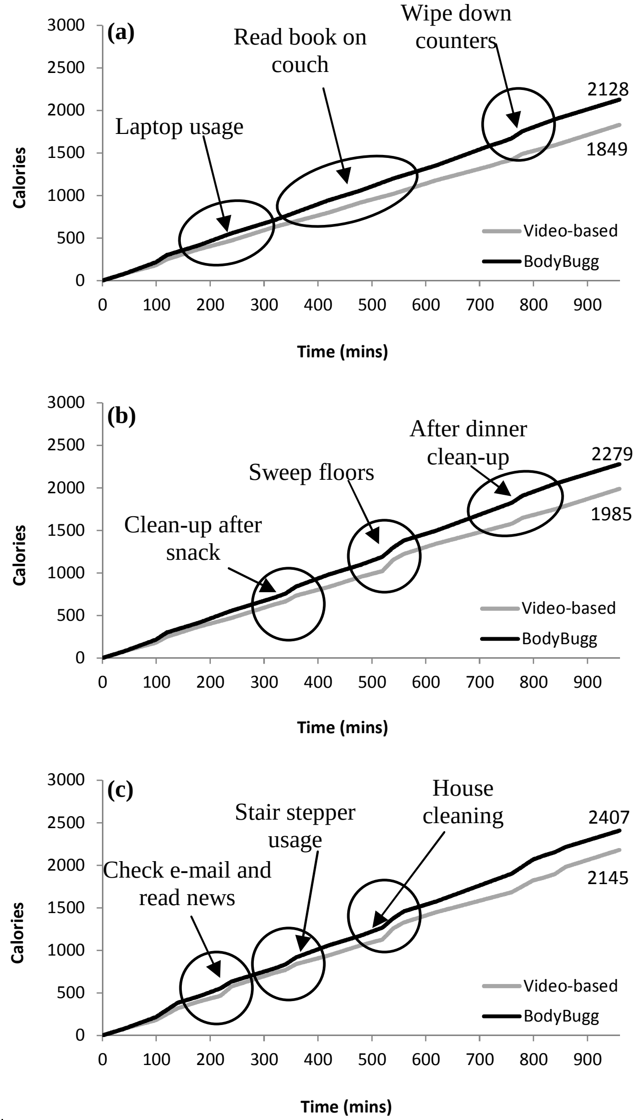
Table 3 shows the low, medium, and high activity level days for each actor. The video-based estimate had a very high fidelity. Notice that the difference between the video-based and BodyBugg energy expenditure estimate for each actor is off by a constant value, e.g., actor 1's video-based energy estimate is about 280 less Calories than the BodyBugg for each day.

Figure 7 represents a low, medium, and high activity day for

Table 3: Fidelity per actor and accuracy of daily energy estimation with one camera compared with BodyBugg energy estimates for a 16-hour day. Fidelity of video-based energy expenditure estimation was nearly perfect. The video-based estimate was different from the BodyBugg by a constant for each actor.

Actor	Activity level of day	BodyBugg estimate (Calories)	Video-based estimate (Calories)	Fidelity per actor	Accuracy
1	Low	2128	1849	r=0.996	86.9%
	Medium	2279	1985		87.1%
	High	2407	2145		89.1%
2	Low	2078	1964	r=1.000	94.5%
	Medium	2217	2079		93.8%
	High	2412	2259		93.6%
3	Low	1993	1974	r=0.983	99.1%
	Medium	2127	2042		96.0%
	High	2331	2273		97.5%
4	Low	2211	1887	r=0.997	85.3%
	Medium	2386	2000		83.8%
	High	2644	2224		84.1%
			Average per actor	**r=0.994**	**90.9%**

Figure 7: Video-based estimated energy expenditure (cumulative) versus BodyBugg for 16-hour days for actor 1, for (a) low, (b) medium, (c) high activity constructed days. Some activities of the day are listed. The video-based energy estimate has very similar slope changes compared to the BodyBugg.



actor 1. The video-based energy estimate has very similar slope changes to the BodyBugg when a new activity began, indicating that video-based energy estimation had identified a change in the activity level. The video-based energy estimate is about 280 Calories less than the BodyBugg energy estimate at the end of each day. Actor's 2 through 4 have a similar trend in that the video-based estimate is less than the BodyBugg estimate.

In some assistive monitoring cases, the user or user's caregiver wishes to accurately know the actual Calories the user expended during the day. Such accuracy may be important in the case of a diabetic patient, for example.

6. Attempted refinements

We attempted a variety of techniques to improve the accuracy of the video-based energy estimate; however, these attempts did not yield significant improvements.

We modified the experiment in Section 5 to include a supplementary camera that had a perpendicular view from the main camera, as shown in Figure 3. The supplementary camera increased the coverage area of the environment. Each camera estimated energy expenditure independently using the trained power regressions per actor from Section 5. We considered two methods for combining camera data: MBR size and Z-score difference. The MBR size method chose the energy estimate at each from the camera with the largest MBR size in view. The camera with the largest MBR is generally the camera that is closest to the person. The Z-score difference method chose the energy estimation at each frame from the camera with the largest change in horizontal acceleration. The camera with the largest Z-score difference is generally the camera with the most observed activity. The MBR size method resulted in an average fidelity of 0.996 and average accuracy of 90.6%. The fidelity was better by 0.002, while the average accuracy decreased by 0.3%. The video-based daily energy estimates were slightly lower with the MBR size method than with the main camera alone. The Z-score difference method resulted in an average fidelity of 0.993 and average accuracy of 85.1%. The Z-score difference method's video-based daily energy estimate were all greater than the BodyBugg daily energy estimate.

We modified the experiment in Section 5 by replacing the main camera during the testing phase with the supplementary camera. The supplementary camera estimated energy expenditure using the trained power regressions per actor from Section 5. The results being an average fidelity of 0.997 and average accuracy of 89.6%. The average fidelity was a 0.003 improvement over the main camera alone; however, the average accuracy decreased by 1.3%. The decreased average accuracy may have been caused by the supplementary camera having had less coverage area than the main camera.

We investigated whether our approach’s estimates could be improved by calibrating the approach to each user. An observation from Section 5 is that each day's energy estimate for an actor was consistently off by the same offset, e.g. 280 Calories for actor 1. One hypothesis is that the offset is caused by the difference in the baseline (at-rest) energy expenditure between one actor and the average of the other actors. We modified the experiment in Section 5 to include a 30 minute calibration phase to determine the baseline energy expenditure for each actor, by recording the BodyBugg energy estimate while the actor sat on the couch and read a book. The resting energy expenditure information was used to determine a constant value by which to add or subtract from the video-based energy estimate. The calculation for the constant value was to subtract an actor's sitting-on-the-couch BodyBugg energy estimate from the average of the other actor's sitting-on-the-couch BodyBugg energy estimate. The average fidelity and average accuracy remained the same at 0.994 and 90.9%, respectively. We also attempted the calibration using a slow pacing activity, which resulted in an average fidelity of 0.995 and average accuracy of 90.8%, and a quick pacing activity resulting in an average fidelity of 0.994 and average accuracy of 90.9%.

7. Limitations and future work

Cameras are not feasible in all locations within a home and do not measure activity outside the home. Thus, the technique may supplement methods requiring a body-worn device or even a mobile phone, those items commonly not used in the home.

We suspect that some of the inaccuracy is due to the inaccuracy of the BodyBugg itself, and we expect accuracy to increase when we get data from a more accurate device.

Future work needs to seek to determine misleading activities, such as a high energy expending activity that is not predicted by the height change, perhaps like lifting heavy objects. Similarly, future work should explore low energy expending activities that are incorrectly predicted to be high energy expending. Future work should determine methods for handling occlusions, such as when a person walks behind a table from the camera's perspective. We also plan to estimate and measure energy for actual full-day in-home activity, especially involving elderly persons.

Future work should detect the particular person that is expending energy, as a person being monitored may have visitors, have a cleaning person or nurse, etc. Similarly, a method for filtering out pets and other motion must also be developed. Further investigation is required to determine the fewest and/or best camera angles that provide good results. A larger training set would also be desirable, especially including elderly persons. The benefits of calibration by entering a persons weight, height, and age should also be investigated.

8. Conclusion

Computing the sum of the MBR's horizontal accelerations is a simple yet effective technique for determining the activity level of a person performing normal activity in the home. The technique yielded nearly perfect fidelity of 0.994 compared to a body-worn BodyBugg device, thus achieving the main goal of determining the relative activity level of different days such that a trend towards lower activity can be detected, followed by possible intervention. Furthermore, the technique yielded average accuracy of energy expenditure of 90.9%. Previous video techniques involved more complex features that required a sufficient view of a person’s head, hands, feet, etc., to classify activities of daily living. In contrast, our sum of the MBR's horizontal accelerations method merely needs a bounding box of motion, and thus can be applied if the person is facing any direction, is likely less sensitive to camera location, and could also be applied to privacy-enhanced video in which a person has been blurred, silhouetted, or even covered by an oval or rectangular shape – all areas to be examined in future work. The technique may supplement or in some cases replace estimations from body-worn devices, which commonly are not worn. Many videos used in this paper are available on the webpage supporting this paper [14]; the complete set will be available in privacy-enhanced form in the near future.

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