CaloriNet: From silhouettes to calorie estimation in private environments

BMVC 2018 Submission # 383

Abstract

We propose a novel deep fusion architecture, *CaloriNet*, for the online estimation of energy expenditure for free living monitoring in private environments, where RGB data is discarded and replaced by silhouettes. Our fused convolutional neural network architecture is trainable end-to-end, to estimate calorie expenditure, using temporal foreground silhouettes alongside accelerometer data. The network is trained and cross-validated on a publicly available dataset, *SPHERE_RGBD + Inertial_calorie*. Results show state-of-the-art minimum error on the estimation of energy expenditure (calories per minute), outperforming alternative, standard and single-modal techniques.

1 Introduction

Physical activity has been linked to general health [22] and has shown positive psychological benefits [9] in clinical tests. Further, sedentary behaviour has consequences that may impose many health risks, for example on musculoskeletal health. This is especially important for older adults, for whom physical activity can counteract the detrimental effect on the cardiovascular system and skeletal muscles associated with age [13]. Monitoring the extent of physical activity via energy expenditure (EE) is therefore of valuable importance and different approaches have been proposed in the literature, from the use of questionnaires [14], to metabolic lookup tables (METs) [1], to peak oxygen uptake estimations [5].

With the development of novel technologies, Internet of Things (IoT) is playing an important role in monitoring well being and health [28]. Accelerometers[1] have often been adopted for the estimation of EE [38], although video monitoring systems have recently showed superior performances [32], especially when combined with inertial based measurements [34]. However, recent works, such as from Birchley *et al*. [7], Ziefle *et al*. [40] and Jancke *et al*. [19] have highlighted the important aspect of privacy concern in medical technologies for smart homes, showing a critical view of such systems from participants. Patients often fear misuse of their video recordings, data leakage or loss due to technical issues. These concerns have been addressed in the work from Hall *et al*. [17] by replacing the RGB video stream with bounding boxes, skeletons and silhouettes, which not only assess the privacy issue, but also allow to scale the amount of data recorded to a size which is more suitable for an IoT platform.

In this paper, we present a fused convolutional architecture, named *CaloriNet*, for the online estimation of EE in private environments, where RGB images are discarded after the generation of silhouettes. Our method uses a data-fusion approach by extracting features

[1]The terms *accelerometers*, *inertial* and *wearable* sensors are used indiscriminately throughout this paper.

from image silhouettes and accelerometer data using a convolutional neural net (CNN), and combining them using fully connected layers to estimate the calorie expenditure. Our approach is based on the evaluation of buffers of data collected over a variable interval of time, allowing an online estimation of calories, rendering the method suitable for energy expenditure monitoring applications. The method was trained and cross-validated on a publicly available dataset [32]. Our results are compared against the latest and most accurate accelerometer EE techniques and more traditional METs lookup tables, obtaining state-of-the-art results.

To stress the importance of our data-fusion approach, we also study the contribution of each modality when used exclusively, by assessing the sub-architectures or branches of our *CaloriNet*. We name these branches *SiluCalNet* and *AccuCalNet*, respectively for the video and the accelerometer modalities alone. While the fusion approach allows a reduction of the overall error from the previous state-of-the-art of 1.21 to 0.88 calories/min, these two modalities are independently able to achieve comparable performances with overall error of 0.98 for *AccuCalNet* and 0.95 for *SiluCalNet*. These sub-architectures are available as standalone alternatives to the fusion approach, making our framework suitable for a vision only or wearable only solution.

2 Background and Related Works

The estimation of EE is a very complex problem, as it is not only related to the physical movement of the subject, but also their metabolism, level of fitness, physiology and environmental conditions, e.g. temperature, humidity and barometric pressure [12]. Considerable effort has been invested in the past for characterizing EE using different types of data, including biometric data (i.e. heart rate monitoring), accelerometers, shoe sensors and cameras. In spite of this variability, EE is strongly correlated with the type of activity which is performed. In 1993, the Compendium of Physical Activities [1] presented a table with different physical activities connected to EE, described as the ratio of working to resting metabolic rates, i.e. METs. These data include detailed description of activities with their corresponding EE values. While METs tables allow a very quick estimation of EE, the approach is based on averages and is only reliable in a statistical sense. Precise measurements of EE are very individual dependent, as different subjects perform activities in distinctive ways and therefore consume a different amount of energy.

To allow an individual-dependent measurement, the work from Ceesay *et al*. [11] proposed a heart rate monitoring method that models their EE. A large body of research has focussed instead on the application of accelerometer data to estimate EE. Some works, such as [2] and [3], make use of activity-dependent models to predict the EE of patients based on the knowledge of the activity they are performing. For a complete review of accelerometer based EE estimation, the reader is referred to Altini *et al*. [4], which investigates the methodologies, sensor numbers and locations to obtain the best EE model. Their work concludes that one single accelerometer close to the subject's centre of mass, combined with an activity-specific estimation model allows for the most accurate and unobtrusive accelerometer-based EE estimation.

One of the most important steps in the use of accelerometer data is the selection of the features. The accelerometer signals are split into contiguous windows, for which a number of frequency and time domain statistics are evaluated, including average, standard deviation, max/min and correlation coefficients, among others [15]. The selection of such hand-crafted features allows the application of standard machine learning algorithms like artificial neural networks [30], random forests [15] and other regression models [26] - with performances strongly dependent on those selected features. Zhu *et al*. [39] proposed the application of CNNs where the raw accelerometer signal was directly fed into a CNN which automatically learned the features that then allowed a multilayer perceptron to produce EE estimates with errors up to 35% lower than methods previous to it. For this reason, Zhu *et al*. [39]'s method was selected as the baseline for comparison with our results.

Computer vision has also been deployed to improve digital health monitoring systems. For example, [20] and [24] attempted to estimate the calories in food by taking single images or short videos of them, although they needed to interact with the user to allow continuous monitoring. Closer to the topic of this paper, Tao *et al*. [34] proposed a vision-based system which estimated calorie expenditure using features extracted from RGB-D image data of humans in action. They showed that RGB-D data can be successfully adopted to estimate EE instead of accelerometers. This work was later extended by replacing their hand-crafted features with CNN-generated features [36], showing an overall reduction of the error. However, as already addressed earlier, it may be critical for healthcare and ambient assisted living (AAL) systems to respect privacy conditions and only provide video sequences in the form of silhouettes [37]. Under such conditions, methods such as [34] are not suitable as they require full RGB-D data to estimate EE.

CNN regression has been successfully applied in computer vision, for example for 3D pose [21], age estimation [25] and viewpoint evaluation [23]. For medical data, CNNs were applied for the segmentation of the cardiac left ventricle, parametrised in terms of location and radius [31]. More recently, a general framework for the analysis of medical images was proposed by Gibson *et al*. [16], to provide a pipeline that allows segmentation, regression (i.e. prediction of attenuation maps in brain scans) and image generation using deep learning.

In this paper, we propose a fused deep architecture which enables the online estimation of EE in privacy-sensitive settings. The method is described in Section 3, including the estimation of temporal silhouettes, the network architecture, and the data augmentation. The dataset, our implementation, and our results are presented in Section 4.

3 Proposed method

We propose *CaloriNet* for online EE estimation, based on the fusion of image silhouettes and accelerometers. The proposal builds on the strengths of two modalities for calorie estimation; (1) visual input that can better recognise the action undertaken [33], yet is at times occluded and associated with privacy concerns, and (2) wearable accelerometers that are light to carry and increasingly popular for healthcare monitoring, but require subject cooperation in wearing and charging the sensors. Thus, we propose an architecture that fuses both modalities, and *importantly* only uses the silhouette (i.e. foreground segmentation) from the visual input, as this provides improved privacy for monitoring in private environments [17].

3.1 Temporal Silhouettes for Calorie Estimation

To support private environments, we propose to limit the visual input to foreground silhouettes. The method we propose here could use silhouettes extracted from RGB foreground segmentation, or depth-based segmentation as used in our experiments. We process the RGB images using OpenPose [10] to detect people and extract the skeletons of the subjects

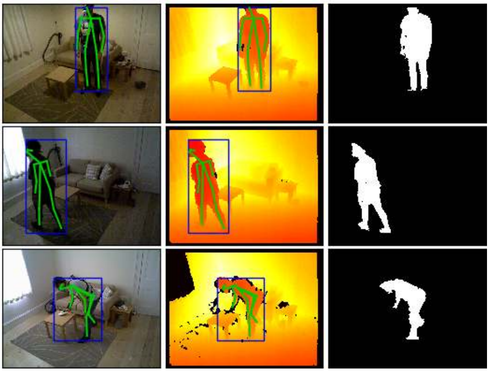

Figure 1: Examples of silhouettes - Colour and depth images were only used to generate silhouettes and discarded after the process.

and then perform clustering on the RGB-D values within each detected bounding box. Some generated silhouettes can be found in Figure 1. The reader is reminded that RGB-D values are only used to generate the silhouettes and are discarded after this process.

The estimation of EE has a strong dependency on monitoring duration, and in particular on the past activities performed. In order to take this into account, temporal modelling and dependency must be included in the network architecture. A typical approach for this problem is to feed a large buffer of images into the network as input, but this would demand a large amount of memory. Since the silhouettes only contain binary information, we decided to pursue a different approach and built an average silhouette using a variable number of images. The idea of transforming a video sequence into a compact representation (to aid our analysis with CNNs) is not new, and previous examples of similar propositions can be found in works such as [8] and [6].

As calorie estimation can be better predicted at various temporal scales, we propose to use a multi-scale temporal template for N time intervals Δt_N of decreasing length, so that:

$$\Delta t_1 > \Delta t_2 > ... > \Delta t_N. \tag{1}$$

For each Δt_k, the silhouettes in the interval $[t - \Delta t_k,\ t]$ were selected and averaged:

$$\bar{S}_k = \frac{1}{\Delta t_k} \sum_{i=t-\Delta t_k}^{t} S(i). \tag{2}$$

This process produces N multi-scale temporal silhouettes $\bar{S}_k$ (one for each Δt), which were then stacked in a 3D tensor S^*, where the 3^{rd} dimension is the stacked multi-scale temporal silhouette:

$$S_t^* \equiv \left\{ \bar{S}_1,\ \bar{S}_2,\ ...,\ \bar{S}_N \right\}\ . \tag{3}$$

S_t^* is then used for the estimation of the calories at time t. This operation allows us to reduce any dependency of the network on the choice of the Δt, facilitating the learning process to pick the correct channels for the best EE estimation for the various daily actions.

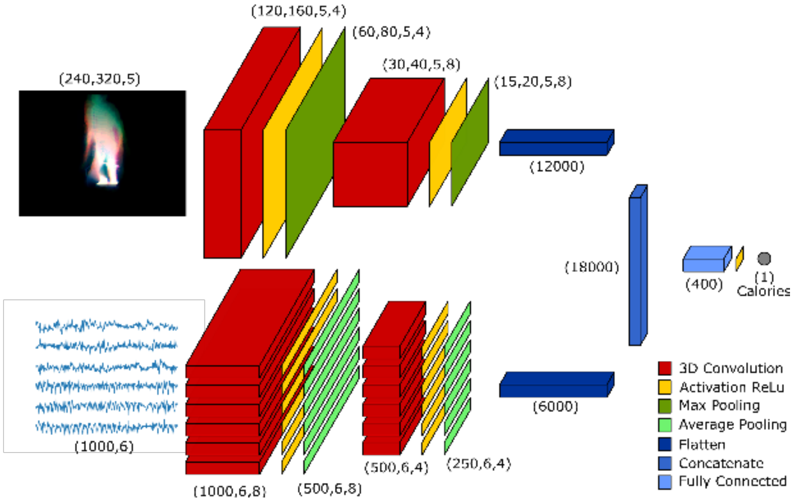

Figure 2: *CaloriNet* - our architecture combines silhouette data (upper branch, *SiluCalNet*) and accelerometer data (lower branch, *AccuCalNet*) to produce calorie estimation.

3.2 Network architecture

The *CaloriNet* architecture is composed of two branches, one for the silhouette data and one for the accelerometer data, as depicted in Figure 2. The network uses two distinct inputs at time t to produce the calorie estimation C_t: the multi-channel average silhouette S_t^* from Eq. (3) and a buffer of accelerometer data in the same time interval $[t - \max_k(\Delta t_k),\ t]$.

A shallow architecture composed of two stacks of layers was adopted. The features extracted from the silhouettes and acceleration were concatenated and fed into one fully connected layer that performs a regression over the calories output. The accelerometer branch was inspired by the work from Zhu *et al.* [39], although several modifications were performed to achieve better performances (see Section 4 for the implementation details). The silhouettes branch also uses two stacks of layers only. In fact, due to the simplistic nature of the data, being originated from binary foreground images and 6-dimensional accelerometer data, any deeper architecture is likely to overfit the input. We empirically found this depth to suffice for the task of the EE estimation.

The network is trained end-to-end using the squared error loss function between the estimated calories C_p and the ground truth C_{GT} over all times t:

$$\text{Loss} = \sum_t \left(C_p^t - C_{GT}^t\right)^2 \tag{4}$$

3.3 Data augmentation

Due to the limited training data, as well as to remove any bias in the recording location, we applied the following data augmentation techniques.

Silhouettes: The typical approach for dealing with subjects moving in a frame is to crop the active area and resize it to a fixed size to use as input for the network [18]. However, this is not suitable for temporal silhouettes as the size of the averaged image depends on the

Figure 3: Sample frames from different subjects and for various activities in the dataset.

motion of the person during the buffered time. To avoid learning specific positions where actions were performed, data augmentation was implemented. During training, images were randomly flipped (horizontally), tilted, and translated (horizontally/vertically).

The data augmentation parameters adopted were determined empirically (see next section). Although the augmented data sometimes resulted in subjects being cropped, this matched situations when subjects were only partially in view of the camera.

Accelerometers: For the accelerometer sensors, inspired by the work from Um *et al.* [35], we randomly changed the magnitude of the sensors by multiplying it with a scalar drawn from a Gaussian distribution with mean 1 and standard deviation 0.1. In addition, the x-y-z channels of each accelerometer were swapped with random permutations.

4 Experiment Details

Dataset — We evaluate our method on the publicly available dataset from [32], namely *SPHERE_RGBD + Inertial_calorie*. This is the only dataset to include RGB-D and accelerometer input with ground truth calorie measurements obtained from a clinical Calorimeter for daily activities. The dataset includes 10 participants, 7 males and 3 females aged between 27.2 ± 3.8 years, with average weight of 72.3 ± 15.0 kg and average height of 173.6 ± 9.8 cm, resulting in average BMI of 23.7 ± 2.8. Each participant was recorded with an RGB-D sensor, two accelerometers (mounted on the waist and the arm) and a COSMED K4b2 portable metabolic measurement system (i.e. a Calorimeter). Eleven activities, as shown in Figure 3, were performed in a predefined sequence: stand still, sit still, walking, wiping the table, vacuuming, sweeping floor, lying down, exercising, upper body stretching, cleaning stain, reading. The dataset presents gaps for some recorded sequences for which we could not generate any silhouettes. Missing data in the training set was therefore replaced by randomly sampling input with the same label from the sequences of the same individual.

Figure 4 presents a visual depiction of the calories recorded in the dataset. Each horizontal bar corresponds to one subject performing the same set of activities. Note that while the calorie measurements present a certain degree of correlation with the activity performed, each subject has a different response in terms of EE when performing the same activity. This difference shows the complexity of the EE problem and highlights the strong limitations of lookup tables when attempting the predict EE for a specific individual.

Implementation details — The network was implemented and trained in Keras using Ten-

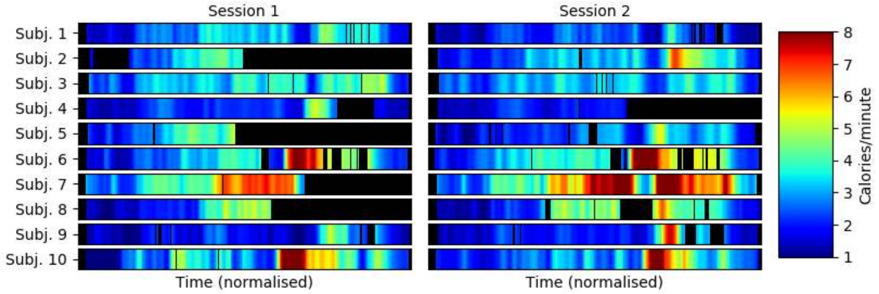

Figure 4: Our visual depiction of the *SPHERE_RGBD* + *Inertial_calorie* dataset. The colour represents the amount of calories/minute, with black areas indicating missing data.

sorflow as backend[2].

Silhouettes: The input to the silhouette branch of the network is a $240 \times 320 \times 5$ tensor, computed over 5 time intervals Δt, defined by,

$$\Delta t_k = \frac{T}{3^k}, \text{ with } k = [0, \ldots, N], \tag{5}$$

where $N = 4$, and T is the maximum buffer size in the multi-scale silhouette image, set to 1000 frames. This choice of value for T is explored in Section 5. Data augmentation was performed using a rotation range of $\theta = \pm 5^\circ$ and a random shift of $t_x = t_y = \pm 20\%$ range. The silhouettes branch of the network architecture, depicted in Figure 2, is formed by two stacks of sequential convolution-activation-pooling layers, followed by a fully connected layer producing the EE. The activation function adopted was a rectified linear unit (*ReLu*), the pooling size was 2 and the stride length for each layer was also 2. Optimal parameters were found by training each network for 1000 epochs and selecting the model with the minimum validation loss after at least 30 epochs of training.

Accelerometers: Using the network proposed by Zhu *et al*. [39] as a baseline for the accelerometer branch of *CaloriNet*, we adopted their architecture of a multi-channel CNN that processes each component of the accelerometer independently, with two stacks of convolution-activation-pooling, using respectively 8 and 4 filters, with a kernel size of 5 and a stride length of 2. We replaced the *tanh* activation function with a *ReLu*, increased the input vector from 256 to 1000 elements and used both the wrist and waist mounted accelerometers as input, combining them into a single 6-channel input. This produced a tensor input of size 1000×6, which was fed into the accelerometer branch of the network. In addition to that, we also estimated the gravity vector using a Wiener filter [29] with a window size of 1 second, and subtracted its direction from the accelerometer data. The baseline model Zhu *et al*. [39] was implemented without the anthropometric feature vector (as we have no heart rate data available), and using both accelerometers as per *AccuCalNet*. We show that each of these modifications allowed a better estimation of the EE in our tests. Our implementation of Zhu *et al*. [39] has higher root mean square error (RMSE) than our proposed modified version in *AccuCalNet* for 10 out of the 11 actions (excluding Wipe), as well as the overall error.

[2] Link to code will be available with the publication.

5 Results

The proposed network *CaloriNet* was tested using leave-one-subject-out cross-validation. As baselines, we also show the results obtained from (a) METs lookup tables [1], (b) previous state-of-the-art on the same dataset from Tao *et al*. [34] which combined hand-crafted visual (full RGB-D images) and accelerometer features with an SVM classifier, and (c) the accelerometer network proposed by Zhu *et al*. [39]. We also report results on single modalities: *AccuCalNet* and *SiluCalNet*. Comparative results are presented in Figure 5, showing the per-activity RMSE between the calories estimated (per minute) and the ground truth, obtained by averaging the errors for each activity class first, and then considering the mean across the subjects. The overall error was instead evaluated by averaging all the RMSEs regardless of the activity performed, by considering the mean across all the subjects.

The figure shows that the EE estimation of the lookup table (METs) produces the highest error, with an overall RMSE of 1.50 cal/min when compared to the Calorimeter device. As already stated, METs tables are based on statistical measurements and are not suitable for subject-specific estimations. Tao *et al*. [34]'s method improves over the the METs table, providing an overall average error of 1.30 cal/min. Zhu *et al*. [39], allows an overall improvement of the error for most of the classes, using accelerometer data only. When compared with the rest of the methods, our proposed *CaloriNet* achieves the best results, producing an error which is almost 30% lower than the result from Zhu *et al*. [39], with a reduction of the RMSE from 1.21 to 0.88 cal/min.

It order to stress the importance of our results, we also provide a comparison of our proposed method when accelerometers (*AccuCalNet*) or silhouettes (*SiluCalNet*) are used independently. Results for *AccuCalNet* already show an overall reduction of the error from 1.21 to 0.98 cal/min showing the advantage of our proposed modifications. The error reduction is particularly pronounced for low-activity classes like *Stand* and *Sit*, which we believe to be due to the high pass gravity filter that we apply to the raw accelerometer signals. A further reduction of the error is achieved by *SiluCalNet*, when silhouettes only are used for the EE, with an overall error of 0.95 cal/min. The RMSE of *SiluCalNet* is particularly improved compared to *AccuCalNet* especially for the *Exercise* and *Stretch* activity classes, as these activities are better characterized by the video sensor.

During our experiments, we noticed that all the methodologies tested struggled to estimate the calorie expenditure during the activities *Exercise* and *Stretch*. We believe this increased error is due to the high inter- and intra-class variance of these activities, estimated to be respectively 7.3 and 2.3 calories/min for the *Exercise* class, and 4.0 and 1.0 calories/min for *Stretch*. These values appear to be between 20 and 60 times higher than the variance shown by other classes like *Sitting* or *Walking*, as a consequence of the rather small training dataset available. A richer dataset including subjects with more different metabolisms and performing a wider range of activities would benefit the reduction of this error.

Sample qualitative results are presented in Figure 6, which shows the continuous calorie prediction for a single individual, evaluated with different algorithms and compared with the ground truth. We observe very good agreement for *CaloriNet* and *SiluCalNet* with the ground truth, while Zhu *et al*. [39]'s method shows quite erratic behaviour, missing the peak measurement of calories during the *Exercise* activity (the red interval in the ground truth). The METs table only provides a step-wise prediction, as it only takes into account the labels of the activities performed, with data missing in those segments where no label was available.

We evaluated the sensitivity of *CaloriNet* when the buffer size parameter T is varied. For this test, we adjusted T to 250, 500, 1000 and 2000 frames, and evaluated the overall error

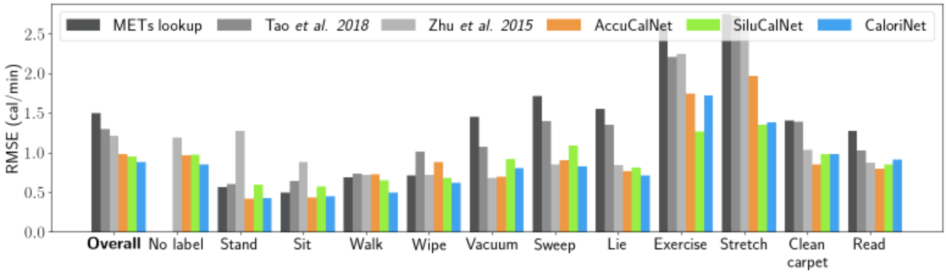

Figure 5: Results in terms of average per-activity RMSE for the calorie estimation.

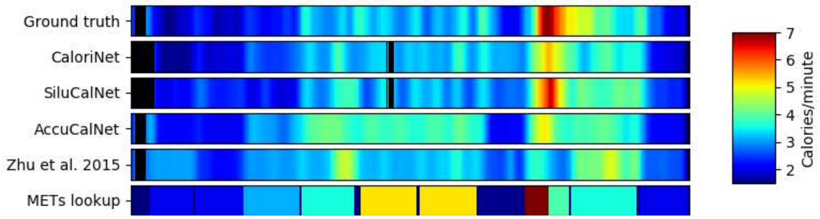

Figure 6: Comparison of the calories measured for a single subject (Subject 2, Session 2) and the prediction obtained with different methods. Black lines depict missing data.

for each buffer size. Results are presented in Figure 7, showing that lower T values produce inferior results while the method is performing consistently for $1000 \leq T \leq 2000$ frames.

6 Conclusions

The increasing adoption of healthcare monitoring devices in AAL environments demands the necessity of privacy-aware video systems. Here, we presented a novel, fused deep architecture for online estimation of energy expenditure using a combination of image silhouettes and accelerometer data. Systems recording such data are, for example, currently being deployed in one hundred homes [27]. Silhouettes were first combined into a multi-channel average image, which provides temporal information for different time lengths. We then fed average silhouettes with accelerometer data in a CNN, that extracted features which were in turn fed into a fully connected layer that estimated the calories expended. We obtained state-of-the-art results in comparison to other existing approaches while protecting privacy.

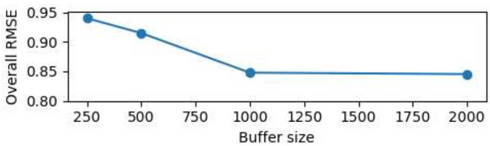

Figure 7: Overall error of *CaloriNet* for different buffer sizes.

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