Who is where? Matching People in Video to Wearable Acceleration During Crowded Mingling Events

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ABSTRACT

We address the challenging problem of associating acceleration data from a wearable sensor with the corresponding spatio-temporal region of a person in video during crowded mingling scenarios. This is an important first step for multi-sensor behavior analysis using these two modalities. Clearly, as the numbers of people in a scene increases, there is also a need to robustly and automatically associate a region of the video with each person's device. We propose a hierarchical association approach which exploits the spatial context of the scene, outperforming the state-of-the-art approaches significantly. Moreover, we present experiments on matching from 3 to more than 130 acceleration and video streams which, to our knowledge, is significantly larger than prior works where only up to 5 device streams are associated.

Keywords

Mingling, wearable sensor, computer vision, association

1. INTRODUCTION

Mingling scenarios involve a dense concentration of people who come together to socialize. Examples of these events are parties, drinks receptions or networking events, and have the potential to hold rich information about how people could potentially influence each other. These kinds of events have received increasing interest from the multimedia, computer vision, and ubiquitous computing communities [6, 13, 5, 8, 1]. However, as the number of people participanting increases they become increasingly challenging to interpret with computer vision alone, due to the difficulties of analyzing the human form under appearance changes, shape deformations and body occlusions.

The use of other modalities, in addition to video, has proven to be a suitable alternative [2, 11]. Thus, each additional modalitiy acts as a complementary source of information in combination with video. For instance, Alameda-Pineda et al. [1] showed improvements in the detection and analysis of free-standing conversational groups by leveraging, along with video, speaking status and proximity using wearable audio and infrared (IR).

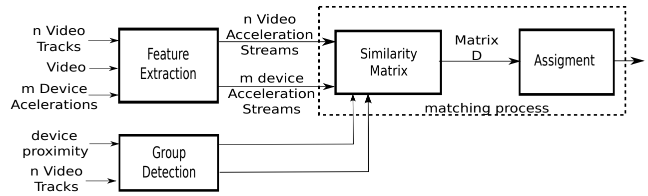

Figure 1: Overview of our approach

Although using wearable sensors as complementary source of information has many advantages, manually associating a specific device to a particular region of the video (where a person is wearing the device) quickly becomes unfeasible as the number of people to be associated increases. So, an automatic association is needed. However, with a higher number of samples to associate per modality the correct associations become harder to discriminate in a short time. Also, mingling events are challenging scenarios where people's social behavior, unlike simple actions like walking, does not tend to have a predictable and easily distinguishable pattern.

In this paper, we associate a time series signal from a wearable accelerometer to a video acceleration stream extracted from a region of video containing the person wearing the wearable device. We chose accelerometers as they are the simplest and most widespread sensors capturing movement.

The main contributions of this paper are: (i) we address large-scale data association in challenging crowded environments, (ii) we propose a novel method based on an extension of the Hungarian algorithm to automatically associate wearable devices via their acceleration reading to its wearer in video (spatio-temporal region) and (iii) we leverage the use of proximity information from the wearable devices and video as a spatial prior to the association process. Using the proximity, we can subdivide the association problem to areas in the real world sharing the same spatial-social context.

The closest works to our own are [15, 10, 9, 12]. Shigeta et al. [10] detected an object which contains an accelerometer out of many moving objects recorded by a single camera, using Normalized Cross-Correlations. Rofouei et al. [9] and Wilson and Benko [15] proposed similar methods to match the accelerometers and gyroscope of a smartphone to the pixels in a 3D video recorded with a Kinect. These approaches can only handle one device at a time and are conceived for scenarios where the person (or object) wearing the device is clearly moving in the video.

Finally, Teixeira et al.[12] identify and localize moving smartphones (by accelerometers and magnetometers) in a

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camera network using a Hidden Markov Models. Although they proposed a solution for more than one device, their experiments have one single person walking under the network of cameras, from which they later 'generate' more participants. They do not address the challenges from a crowded scene making their solution infeasible for mingling groups.

Compared to these works, our approach proposes a considerable increase in the number of accelerometers to be associated. To the best of our knowledge, we are the first to consider the association of video with multiple wearable devices in such crowded scenarios and with more than 5 device streams. In addition, we propose to solve the association problem in a much more challenging context where people's behavior can not be as easily characterized (e.g. walking).

2. OUR APPROACH

Our approach is summarized in Fig. 1 and detailed below.

2.1 Feature extraction

For a wearable device, a single acceleration stream is obtained using the magnitude of the 3 axes. Each axis is first normalized using its mean and variance over the entire time.

To associate each device stream with a region containing a person all the regions of interest (or bounding boxes), which include a person, are first extracted. Then, we concatenate the bounding boxes over time for each person, which results in the track (area over time) for that person. The Vatic tool [14] for video annotation was used to extract the bounding boxes. Using the SPOT tracker [16] gave us similar results but since this work only focuses on the already challenging problem of associating large numbers of streams and not in tracking we chose a manual labeling tool.

Next, for each track, an acceleration stream is calculated as follows. First, we extract dense optical flow for the video. Then, for each frame, we take the magnitude of all the flow vectors inside the box and compute the mean for those with a magnitude greater than zero. Thus, we obtain a vector of mean flow magnitudes for a given track over the entire video of length T samples, which represents the speed of movement for that person.This captures the influence of fine grained movements, originating from subtle social behavior such as gestures or laughter, as well as movement of the entire body. Fig. 2 illustrates the input and output of this step for 3 tracks (subjects). Finally, we compute the acceleration vector from the speed using finite difference approximation.

After we extract the acceleration streams from the video and wearable devices, we proceed to treat each stream as follows. First, we normalize the maximum value of all streams to one, so a comparison between video and wearable acceleration can be made. Next, we apply a sliding window calculating the variance over each stream. Using this instead of the raw acceleration gave us a better representation of changes in movement activity of each person.

2.2 Similarity measurements

Both video and acceleration streams are noisy because they capture only partially the behavior of a person. Therefore, we need measurements to assess how similar 2 streams are and not if they are equal. Different widely used [4] metrics are compared to quantify the affinity between the acceleration streams from video and the devices: covariance (COV), Dynamic Time Warping Distance (DTW) and Mutual Information (MI).

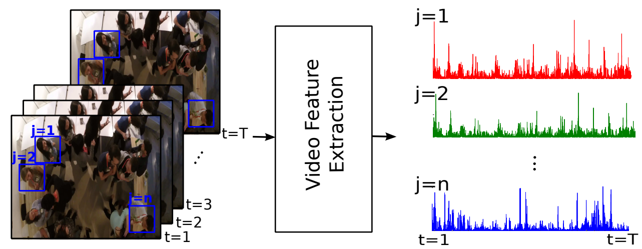


Figure 2: Feature extraction from video for 3 example tracks (subjects). Output: speed stream for each participant for interval of length T

2.3 Assignment methods

We consider the matching process to be an assignment problem where m elements of a set M (device streams) need to be associated with n elements of a set N (video streams), by fulfilling a given function or constraint. A distances matrix $\mathbf{D}$ (size $m \times n$) is formed by the pairwise distances between all possible combinations of m acceleration and n video streams, where

$$\mathbf{D}_{ij} = d(i,j), i \in \{1 \cdots m\} \text{ and } j \in \{1 \cdots n\} \quad (1)$$

and d is one of the similarity metrics from Section 2.2.

Winner-takes-all (greedy) association
State-of-the-art methods ([10, 9, 15]) use a greedy approach where the element in $\mathbf{D}$ that has the highest value determines the assignment. The corresponding column and row are removed from $\mathbf{D}$ and the assignment process is repeated, if applicable. This will be our baseline.

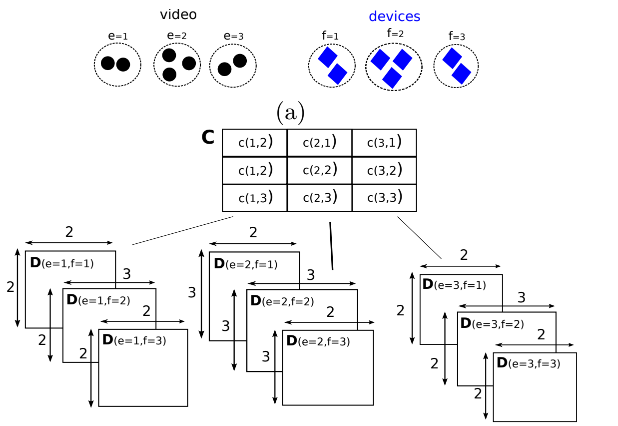
Hungarian method
Although the winner-takes-all method is a reasonable baseline, it does not consider that there is likely to be noise in both sensor streams. Hence, it may not be able to distinguish one possible assignment from the other. This is particularly problematic as the number of streams increases. Trying to optimize the assignments globally may help.

The Hungarian method [3] computes a solution for the assignment problem by optimally matching the elements m and n, based on a global optimization of $\mathbf{D}$. For this assignment problem, given the matrix of distances $\mathbf{D}$, the aim is to find the global cost c that minimizes

$$c = \min_{S^* \in S} \sum_{i=1}^{m} \sum_{j=1}^{n} d(i,j) w(i,j) \quad (2)$$

where $w(i,j)$ is the binary weight for matrix $\mathbf{W} \in \{0,1\}^{m \times n}$ for the element (i,j), and S is the set of all matrices $\mathbf{W}$ that fulfill 3 constraints: (i) no more than one weight equals to 1 per column so $\mathbf{W}\mathbf{1}_n \leq \mathbf{1}_m$, (ii) no more than one weight equals to 1 per row so $\mathbf{1}_m^T \mathbf{W} \leq \mathbf{1}_n^T$ and (iii) the total number of weights sums to one such that $\mathbf{1}_m^T \mathbf{W} \mathbf{1}_n = min(m,n)$. Thus, the elements of sets M and N can only be paired once and the method chooses the set of pairs with the lowest total pairing cost. Several solutions exist to solve this problem [3].

Hierarchical Hungarian method
As the number of people increases, there is a higher probability of finding similar streams. It is desirable for a potential real-time application to be able to rely on shorter time intervals to make the association. But if the streams are too short, we will not have enough observable behavior for the distance metric to be discriminative.



(b)

Figure 3: Example of assignment method. (a) Devices and Video streams representations. The dotted circles show the group detection. (b) Our proposed *Hierarchical Hungarian* method using the streams and clusters from (a).

As a solution, we hypothesize that subdividing the problem based on the local spatial neighborhood in each sensor modality can improve the numbers of correctly associated streams, which exploits the spatial and social context of the gathering. Thus, we propose an extension to the Hungarian method by performing the assignment in a hierarchical manner, using a divide-and-conquer strategy. All streams are subdivided into groups in each modality, reducing the initial assignment problem from a global to local optimization, defined by the number of groups in each modality.

So, the n video and m accelerometer streams are clustered into p groups for the acceleration and q groups for the video streams, as seen in Fig. 3(a). Then, $p \times q$ different distance matrices are generated; one for each group combination (e, f) where indices $e \in \{1 \cdots p\}$ and $f \in \{1 \cdots q\}$. For each of these matrices, the corresponding stream assignment is calculated. Within each group-to-group matching, the possible stream combinations are now reduced to $n'_e \times m'_f$, where n'_e and m'_f are the number of elements in the e^{th} and f^{th} device and video groupings, respectively.

Each group-to-group assignment cost $c(e, f)$ is then obtained by Eq.2 and placed in a new matrix $\mathbf{C}$ (see Fig. 3(b)), which represents the costs of assigning the elements within each possible group combination e and f. Each cost $c(e, f)$ must be normalized by dividing by the number of assignments made so $\mathbf{C_{ef}} = c(e, f)/\min(m'_f, n'_e)$. For example, when comparing a group of 3 streams against a group of 2, only 2 costs from the 3×2 matrix are used for the final assignment. Finally, the Hungarian algorithm is applied to matrix $\mathbf{C}$ to find the optimal group-to-group assignment. The stream assignment for that specific group-to-group pairing is then chosen. Our Hierarchical Hungarian assignment procedure is illustrated in Fig. 3.

2.4 Clustering Devices and Video Streams

We propose to generate the groups by clustering based on their proximity over a particular time interval. The group detection must be performed independently per sensor type.

Each of the devices outputs a dynamic binary proximity graph (see Section 3), which is later refined to eliminate false neighbor detections using the method proposed by Martella et al. [7]. To do so, they apply a density-based clustering to group all the neighbor detections in time (see [7] for more details). Finally, maximal cliques are identified from the proximity graph to obtain p sets of fully connected nodes. We choose maximal cliques as this clustering method has proven to be an accurate approximation for conversational groups [6].

To cluster the video streams, we use the tracks extracted for each of the participants. For each frame of the video, an affinity matrix $\mathbf{A}$ is created, which defines a symmetric distance between person i and j $\mathbf{A}_{ij} = -e^{\frac{d_{ij}}{2\sigma^2}}$ where d_{ij} is the Euclidean distance in the image plane between the centroids of the bounding boxes for person i and j and σ is the width of the Gaussian kernel. In our experiments, σ was set to 150 pixels, as this was an approximate value for group distance given the image size and resolution of the camera. Then, we apply the group detection algorithm that extracts clusters as maximal cliques in edge-weighted graphs [6].

This is an iterative procedure that optimizes the group clustering based on the notion of a dominant set. If we have a graph G with each node representing the centroid of a person's bounding box and the affinity between people to be the edges, we can consider a representation of the closeness of a subset S of the graph as follows. We define a measure called the average weighted degree of a vertex $i \in S$ with respect to set S as $k_S(i) = \frac{1}{|S|}\sum_{j \in S} a_{ij}$. The relative affinity between node $j \notin S$ and i is defined as $\phi_S(i, j) = a_{ij} - k_S(i)$, and the weight of each i with respect to a set $S = R \cup \{i\}$ is defined recursively as

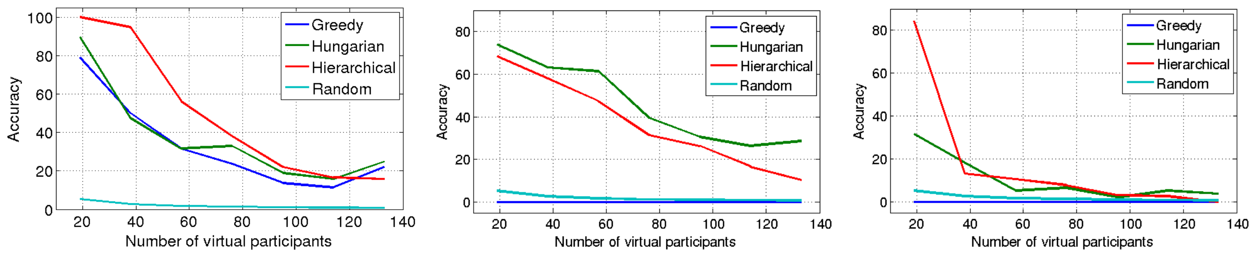
$$w_S(i) = \begin{cases} 1 & \text{if} |S| = 1 \\ \sum_{j \in R} \phi_R(j, i)\, w_R(j) & \text{otherwise} \end{cases} \tag{3}$$

$w_S(i)$ measures the overall relative affinity between i and the rest of the vertices in S, weighted by the overall affinity of the vertices in R. Therefore to find the cliques in the graph $w_S(i) > 0, \forall i \in S$. For every graph, only one maximal clique can be identified at a time and a peeling strategy is employed where the same conditions are repeatedly applied to the remaining sub-graph until no more cliques remain. Finally, the cliques identified per frame are combined into a single set of groupings using majority voting.

3. DATA

We collected video and wearable acceleration for 30 participants during a group gathering. This data was collected in a real mingling scenario after a speed dating event, where people were encouraged to mingle. Each person wore a wearable device hung around the neck which recorded triaxial acceleration at 20 Hz. These devices also have a binary proximity detector based on beacon communication with other devices. Thus, each device emits its own ID to all other devices around it allowing the devices to synchronize every second and detect each other from 2-3 meters away. The detection of a device is considered as a proximity detection (binary signal). Finally, overhead video was captured using 5 different GoPro Hero 3+ cameras that covered the whole mingling area with some overlap.

Due to hardware malfunction only 28 devices recorded data during the event. Also, people entering the field of view for just a small interval of time or those who's appearance was only captured partially for the camera (less than 50%) were excluded, as we do not intend to evaluate the impact of heavy visual occlusion in the matching process yet. After



(a) (b) (c)

Figure 4: Accuracy of the stream association for our proposed method (Hierarchical), the state-of-the-art (Hungarian and Greedy) and a random baseline (Random) using (a) COV, (b) DTW and (c) MI.

Table 1: Association accuracy of the Hungarian and Hierarchical Hungarian method using 100s intervals using the COV

$N^{\underline{o}}$ Partic.	19	38	76
Hungarian	47.37	36.84	29.83
Hierarchical	**73.68**	**76.32**	**39.47**

these restrictions, we have video and acceleration streams for 19 subjects, for about 6 minutes.

4. EXPERIMENTS AND RESULTS

4.1 Generating virtual streams

Although significantly higher than those in previous works, our number of subjects is still rather low. To go further, we used *virtual streams*, similarly to Teixeira et al. [12], by splitting the total time interval of the streams into smaller intervals and treating each one as if they were occurring at the same time. Unlike [12], our data contains densely crowded mingling behavior so the dense crowding property holds across the virtual participants. From our 19 original streams, we created subsets with 38, 57, 76, 95, 114 and 133 virtual subjects, increasing significantly the number of streams we could associate. This leads inevitably to a reduction in the length of the streams, which is a trade-off that we also study in the following section.

4.2 Results

Fig. 4 shows the assignment accuracy against the number of participants for the 3 assignment methods in Section 2.3 and the metrics in Section 2.2. To stress test the number of streams to associate, we generate up to 133 virtual participants. Note that by repeatedly splitting the interval by a factor from 1 to 7 we have a time interval of 360s for 19 participants (original data), 180s for 38, and up to 51s for 133 participants for these figures.

Comparison between assignment methods

As seen in Fig.4, both Hungarian approaches performed significantly better than the random baseline when using the COV and the DTW metrics. Furthermore, our Hierarchical approach tends to have a higher accuracy than the other 2 methods when using the COV for less than 80 participants.

These results, although promising, are obtained using increasingly shorter intervals of the virtual streams. Due to this, Table 1 shows the accuracy for the two Hungarian-based methods using the same length of 100s for all streams and the COV as metric. For this test, given the data available, we can only split our data into 3 sets of virtual streams. Here, our Hierarchical Hungarian method still outperforms the Hungarian method, so the interval length is not necessarily the reason for the higher accuracies.

Table 2: Upper bound case: assignment accuracy using the Hierarchical Hungarian assignment where the correct group-to-group matching is known.*

	$N^{\underline{o}}$ Partic.	19	38	57	76	95	114	133
Acc(%)	COV	**100**	**94.7**	**89.5**	**82.9**	**81.1**	**86.0**	**79.7**
	DTW	**100**	89.5	80.7	82.9	75.8	82.5	75.2
	MI	84.2	76.3	56.1	64.5	67.4	66.7	66.9

*Group-to-group matching is manually annotated

Although outperforming the other methods, the accuracy for our Hierarchical Hungarian method decreases with a higher number of participants. We hypothesize that as the number of groups increases but the observation time remains low, the method will now have problems to discriminate between the groups instead of streams. Table 2 summarizes the assignment accuracy for all the metrics and different virtual streams using an ideal group-to-group matching, where the groups are matched manually based on the ground truth, instead of the matches chosen automatically by our method.

These results represent the upper bound for our Hierarchical method and suggests that the errors in Fig. 4(a) are introduced by the group-to-group matching, implying that a minimum time is needed to discriminate between groups.

Comparison between metrics

The performance for the Hierarchical Hungarian method is better overall than the Hungarian method when using for the COV but not so for the DTW distance. This implies that, unlike the COV, the costs chosen as globally optimal for assignments using the DTW are very similar between each other, making the matrix $\mathbf{C}$ noisy and difficult to discriminate for the Hierarchical Hungarian method. A particularly interesting result is the low accuracy achieved when using the MI as the similarity metric. However, previous works have shown that when 2 people interact, their MI tend to increase [4]. Thus, due to this and our rather short intervals, this metric it might not be adequate in our case.

5. CONCLUSION

We show a novel method for associating wearable devices to the region in the video of the person wearing the device, using its acceleration and radio-based proximity. We also have shown that using the spatial and social context as a pre-processing step for accelerometer and video stream matching increases the accuracy of our association method, particularly as the number of candidate streams increases. This leads to an increase in the matching accuracy of 47% when the spatial context was exploited for 38 participants. The number of devices used represents a considerable increase compared to previous efforts. In addition, we proposed an empirical validation for extending further the amount of devices to associate.

6. REFERENCES

[1] X. Alameda-Pineda, Y. Yan, E. Ricci, O. Lanz, and N. Sebe. Analizing free-standing convers. groups:a multimodal approach. *ACMMM*, 2015.

[2] G. Bahle, P. Lukowicz, K. Kunze, and K. Kise. I see you: How to improve wearable activity recognition by leveraging information from environmental cameras. *PerCom*, 2013.

[3] B. Burkard, M. D.'Amico, and S. Martello. *Assignment problems*. 2009.

[4] E. Delaherche, M. Chetouani, A. Mahdhaoui, C. Saint-Georges, S. Viaux, and D. Cohen. Interpersonal Synchrony: A Survey of Evaluation Methods across Disciplines. *Trans. on Affective Computing*, 2012.

[5] T. Gan, Y. Wong, D. Zhang, and M. Kankanhalli. Temporal encoded F-formation system for social interac. detection. In *ACMMM*, 2013.

[6] H. Hung and B. Krose. Detecting F-formations as dominant sets. *ICMI*, 2011.

[7] C. Martella, M. Dobson, A. van Halteren, and M. Van Steen. From proximity sensing to spatial-temporal social graphs. *PerCom*, 2014.

[8] C. Martella, E. Gedik, L. Cabrera-Quiros, G. Englebienne, and H. Hung. How Was It? Exploiting Smartphone Sensing to Measure Implicit Audience Responses to Live Performances. In *ACMMM*, 2015.

[9] M. Rofouei, A. Wilson, A. Brush, and S. Tansley. Your Phone or Mine? Fusing Body, Touch and Device Sensing for Multi-User Device-Display Interaction. In *CHI*, 2012.

[10] O. Shigeta, S. Kagami, and K. Hashimoto. Identifying a moving object with an accelerometer in a camera view. In *IROS*, 2008.

[11] S. Stein and S. Mckenna. Comb. embedded accelerometers with computer vision for recogn. food preparation activities. *UbiComp*, 2013.

[12] T. Teixeira, D. Jung, and A. Savvides. Tasking networked CCTV cameras and mobile phones to identify and localise multiple persons. *UbiComp*, 2010.

[13] S. Vascon, E. Mequanint, M. Cristani, H. Hung, M. Pelillo, and V. Murino. A Game-Theoretic Probabilistic Approach for Detecting Conversational Groups . In *ACCV*, 2014.

[14] C. Vondrick, D. Patterson, and D. Ramanan. Efficiently Scaling Up Crowdsourced Video Annotation. *IJCV*, 2012.

[15] A. Wilson and H. Benko. CrossMotion:fusing device and image motion for user identif., tracking and device association. In *ICMI*, 2014.

[16] L. Zhang and L. Van Der Maaten. Structure Preserving Object Tracking. *IEEE CVPR*, 2013.