Modelling of Pedestrian Groups and Application to Group Recognition

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Abstract - In analysing the movement and interaction of pedestrians it is very important to take into account the social groups they form. In this paper we describe the work we have done on the modelling of the spatial formations of socially interacting groups of pedestrians. We than explain the application of the obtained statistical models to the automatic detection of pedestrians who are in a group. The results show that a high detection accuracy can be achieved.

I. Introduction

Knowing the behaviour and state of people in an environment is important for applications such as security, surveillance [1,2], providing services [3] or the use of socially interacting robots and other autonomously navigating vehicles, like wheelchairs or delivery carts [4,5]. A large part of pedestrians move in groups [6] and present a specific behavioural and dynamical pattern [7]. For most of these applications it would be very useful to recognise pedestrians that move as part of groups, both for robot navigation purposes (since groups move in a different way and thus robots have to take into account such characteristic behaviour) or service and surveillance tasks (since groups exhibit specific behaviour and interests that are different from those of individuals).

Automatic detection and tracking of pedestrians using cameras [8] or range sensors [9] has recently become possible, but the automatic recognition of groups is still an open problem. In recent years a few works performing group recognition based on analysis of similarity and proximity in motion [10-12] have been proposed. The shortcoming of this approach is that it does not allow for identifying pedestrians who are actually *socially interacting* (and not just moving together), which are in general the target of the surveillance, service, and, since interacting groups have a strong tendency to keep on moving together, navigation applications. Furthermore, human observers generally do not need to examine a full trajectory to recognise interacting groups, since they can hint their nature based on visual clues such as conversation and gazing [13-15].

Although such clues are usually not available to tracking systems, the work in [7] showed that interacting groups move with a specific spatial and velocity structure, and thus their identification is possible also through a common tracking system. The works by Yücel et al. [16-19] already investigated the possibility of using pedestrian pair relative positions and velocity to recognize interacting groups and distinguish them from unrelated pedestrians or human-object (e.g. carts) pairs. Nevertheless, their works 1) combined a set of observations to obtain a binary evaluation of the nature of the pair, 2) did not take advantage of the theoretical and empirical insights like the ones described in [7], and 3) operated recognition in a fixed square area.

In this work we will build on the results of [7] to obtain a system that, in an arbitrary pedestrian environment and possibly based on a single observation, may provide us with the *probability* that a pedestrian pair is part of a group or not. Having the probability instead of just a binary yes-no classification is useful because it allows for better dealing with ambiguous situations. The recognition will be based on pedestrian pairs because walking groups of size larger than 4 do not present long lasting interaction and usually split in groups of 2 or 3 [20]. Furthermore we will assume that the structure of 3-people groups may be inferred by pairwise interaction, as suggested in [7]. This assumption will be examined again in the results section.

II. Pedestrian Groups Dataset

The pedestrian data that was used in this work was collected by tracking pedestrians during 2 days in two large straight corridors which connect the *Diamor* shopping centre in Osaka, Japan, with the railway station. The tracking was done using an automatic tracking system described in [21], which used multiple laser range finders distributed in the environment. The collected pedestrian data was then analysed by one coder, who manually labelled pedestrians that were part of a group.

The whole dataset with pedestrian trajectories and labelled groups is freely available and can be downloaded from http://www.irc.atr.jp/sets/groups/. (It also contains pedestrian data taken in a different environment, but that one was not used in this work.)

III. Group Modelling

Analysis in [20] has shown that two pedestrians who are socially interacting in a walking group tend to have a stable abreast formation, i.e. they walk in such a way that the direction of movement is perpendicular to the direction towards the partner. In [7] a theoretical model for this formation was proposed, which considered the

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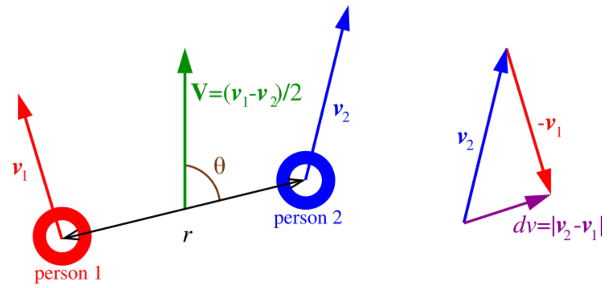

Figure 1. Definition of used observables.

necessity of members of interacting groups to keep both their walking goal and interaction partner in their field of view, and this was compared and validated against empirical observations of pedestrian groups. In the resulting model if the relative position of a pedestrian pair is studied using polar coordinates in the "centre of mass frame" (or better just the average position frame, since to each pedestrian is assigned a fictitious mass m=1), the spatial structure of a 2-people interacting group assumes a simple form. Following Fig. 1, we define r to be the distance between pedestrians and $\theta \in [-\pi\ \pi]$ the angle between the line connecting the pedestrians and the group velocity vector **V**, equal to the mean of the velocities of the two pedestrians, i.e. $(\boldsymbol{v}_1+\boldsymbol{v}_2)/2$. The probability distribution for the interacting pedestrian's relative position can then be written as proportional to the following expression [7]:

$$p_{\mathrm{I}}(r,\theta) \propto r\exp(-R(r))\exp(-\Theta(\theta)). \qquad (1)$$

(Note that this also shows that r and θ are statistically independent variables.) The functions R and Θ in (1) are given by:

$$\begin{aligned} R(r) &= A(r_0/r + r/r_0), \\ \Theta(\theta) &= B(\theta - \mathrm{sgn}(\theta)\pi/2)^2, \end{aligned} \qquad (2)$$

The parameters A, B and r_0 depend on the environment and pedestrian density [22-24]. For example, when the density of pedestrians is higher, people in a group will tend to stand closer to each other, which would result in a different function R. We therefore do not try to model the functions in (2) explicitly but rely on the empirical distributions computed as frequency histograms. In other words, for each environment we gather pedestrian data and for the interacting pedestrian pairs we calculate the observed probability distributions $p_{\mathrm{I}}(r)$ and $p_{\mathrm{I}}(\theta)$. The probability in (1) then becomes:

$$p_{\mathrm{I}}(r,\theta) = p_{\mathrm{I}}(r)\,p_{\mathrm{I}}(\theta). \qquad (3)$$

For non-interacting groups, assuming isotropy of the environment and taking in account the finite size of the human body, we may model the probability distribution as a uniform one for $r > \delta$ (= 0.5 m), i.e. using the polar Jacobian:

$$p_{\mathrm{NI}}(r,\theta) = \begin{cases} Cr & \text{if } r > \delta \\ 0 & \text{otherwise} \end{cases} \qquad (4)$$

so that r and θ are again independent. Although the isotropy condition is quite strong, it appears to work reasonably well also for a bidirectional corridor like the *Diamor* environment, and we decided to use it due to its simplicity (there is no need of calibration or learning from collected pedestrian data). Since $p_{\mathrm{I}}(r) \approx 0$ when pedestrians are sufficiently far away from each other, we can assume pedestrians to be non-interacting if their distance is larger than a fixed value R_{MAX} (= 3 m), which can be used to speed up the calculations.

Paper [7] studied also absolute velocity distributions, which were indeed different between groups and individuals, but their difference did not result to be strong enough for a stable recognition. We thus decided to compute, for both interacting and non-interacting pedestrians, the probability distribution of the magnitude of velocity difference dv (Fig. 1), since this value turned out to be clearly different for the interacting and non-interacting pairs:

$$dv = |\boldsymbol{v}_1 - \boldsymbol{v}_2|. \qquad (5)$$

Using this value can be compared to the approach of [16], which used the scalar product of velocities $(\boldsymbol{v}_1 \cdot \boldsymbol{v}_2)$. However the velocity difference allows us to recognise pedestrians moving in the same direction but at different velocities (such as one pedestrian overtaking the other one) even with a single observation. One may still wish to use the scalar product as a preliminary binary condition (i.e. if the scalar product of the pedestrian velocities is negative they are clearly non-interacting) for computational economy.

The variable dv is also assumed independent from both r and θ, so with the addition of the probability distribution $p_{\mathrm{I}}(dv)$ (which also needs to be calculated from observations of pedestrians), the total probability for interacting groups becomes:

$$p_{\mathrm{I}}(r,\theta,dv) = p_{\mathrm{I}}(r)\,p_{\mathrm{I}}(\theta)\,p_{\mathrm{I}}(dv). \qquad (6)$$

Apart from non-interacting and interacting pairs (denoted below as 'non-group' and 'group' relationships), we considered also another type of pair – that of a person pushing a wheelchair, a baby buggy or pram, or a cart. Compared to the interacting pairs, this type is different in that the two people are moving one after the other. We name this a 'cart' relationship. (Although carts are not people we included them here because our tracking system did not distinguish between humans and non-humans.) The probability of belonging to a 'cart' type of group $p_{\mathrm{c}}(r, \theta, dv)$is calculated in a similar way as for interacting groups in (6), where the corresponding probabilities are again estimated based on observed data.

Fig. 2 shows an example of the probability distributions of the observables θ, r, dv, for each of the three types of relationships we considered. They were obtained based on the collected data described in section II, except for the angle θ and radius r in the 'non-group' which were based on the theoretical model (5). There is obviously a large difference in the distributions between the 'non-group' and the other two cases, which suggest that it should be easy to distinguish between them. On the other hand the 'group' and 'cart' relationships mainly differ in the angle θ, which reflects the fact that interacting group pairs walk abreast while the 'cart' pairs move one after the other.

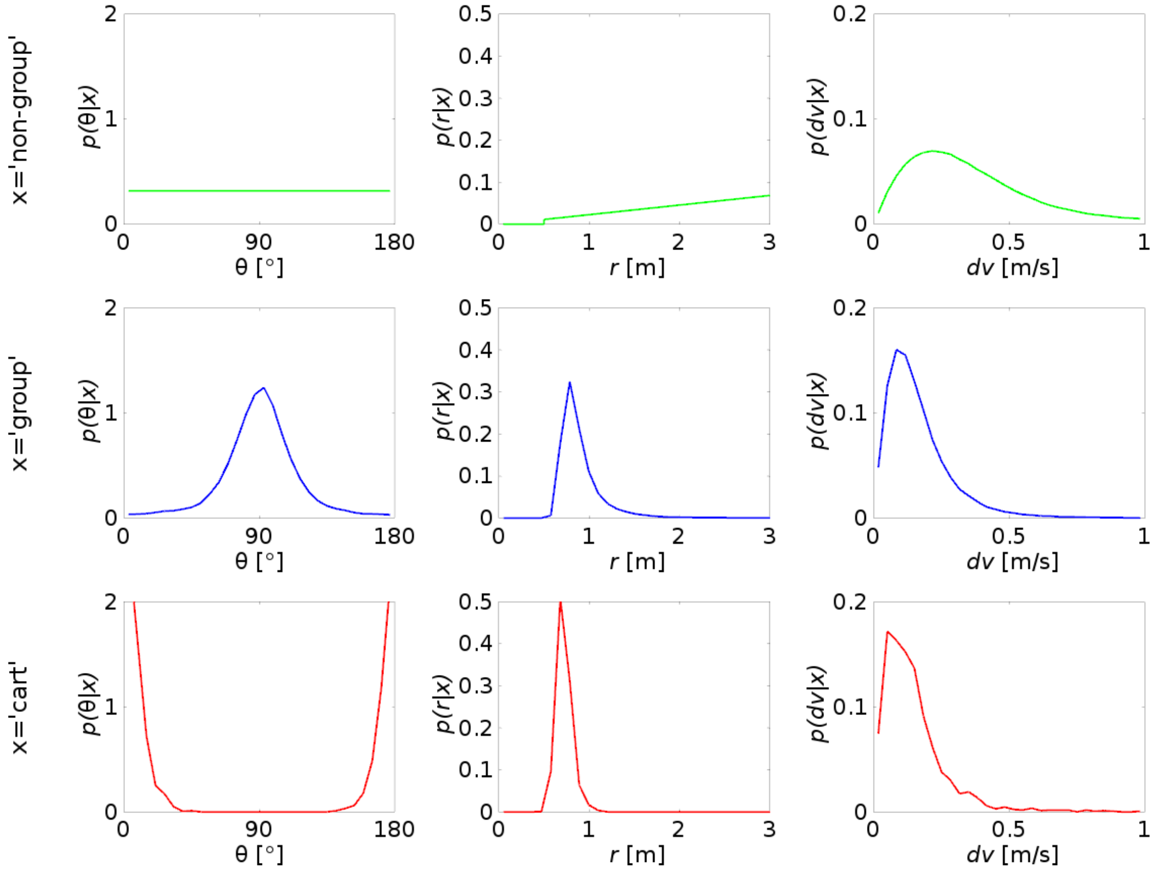

Figure 2. Learned conditional probabilities.

IV. Estimation of Group Membership

We wish to estimate the group membership probabilities, or to be more precise, the conditional probabilities $p(x|z)$, where x is one of 'non-group', 'group' or 'cart', and z is used here to denote the "measurement", i.e. $z = \{\theta, r, dv\}$. Making use of the Bayes' formula the group membership probability can be estimated as:

$$p(x|z) \propto p(x)\, p(z|x). \tag{7}$$

Here $p(x)$ is the prior probability for the group membership and $p(z|x)$ is the conditional probability (likelihood) of obtaining specific values for the observables depending on the case x. (The proportionality in (7) means that the final probabilities need to be normalized so that their sum is 1.) Using the fact that θ, r, and dv are independent variables, as discussed in the previous section, we have that:

$$p(z|x) = p(\theta|x)\, p(r|x)\, p(dv|x). \tag{8}$$

The conditional probabilities on the right-hand side correspond to the ones plotted in Fig. 2. As described in the previous section they can be obtained by collecting pedestrian data and calculating the resulting probability distributions for θ, r, and dv, separately for pedestrians not in a group, pedestrians in a group and cart-pedestrian groups. Concerning the prior probability p(x), since it represents the probability of group membership without any external knowledge, a good value for it can be the observed relative frequency of non-groups, groups and carts, which can also be obtained from the collected and labelled pedestrian data.

At each instant, based on the observed values of θ, r and dv for a specific person and people surrounding her, it is possible to use (7) and (8) to calculate the probabilities for group membership. This will be called the <u>instantaneous estimate</u> in the following text.

Another approach is to have a recursive Bayesian estimation, where instead of using the same fixed prior $p(x)$ at every instant one can make use of the estimated probability from the previous time step as a better representative of our prior knowledge about the probability at the current instant. In that case (7) becomes:

$$p(x_k|z_k) \propto p(x_k|z_{k-1})\, p(z_k|x_k), \tag{9}$$

where the index k stands for the time instant. The factor $p(x_k|z_{k-1})$ in this expression is the predicted probability at step k based on the measurements up to the previous step k-1. For that we use the estimated group membership probability from the previous step. However, we reset it partially toward the default prior value $p(x)$, to reflect the fact that the we are less certain when predicting the probabilities for one step ahead:

$$p(x_k|z_{k-1}) = (1-\alpha)\, p(x_{k-1}|z_{k-1}) + \alpha\, p(x). \tag{10}$$

Here $\alpha \in [0\ 1]$ is a factor which defines how quickly the estimator "forgets" the previously estimated value. Larger values of α correspond to quicker forgetting, and for α = 1 the recursive estimate is equivalent to the instantaneous

TABLE I. RESULT OF DETECTION OF GROUPS

Relationship		Correct classification instantaneous	Correct classification recursive
Non-group		96.6%	96.6%
Groups	2-person	90.6%	91.9%
	3-person	69.6%	73.0%
Cart		92%	96%

one. Combining (8), (9) and (10) the estimated probability can be recursively updated from step to step (recursive estimate).

Finally, in order to make a classification based on the group membership probabilities it is enough just to chose as classification result the one type of relationship x for which the estimated $p(x|z)$ is higher then the other two cases.

V. RESULTS

To evaluate the estimation of the probability of belonging to a group we first trained the model on 20% of the dataset. The conditional probabilities plotted in Fig. 2 were obtained like that. Based on the observed data the prior probability $p(x)$ was set to the relative frequencies of non-group, group and cart pairs, which were 0.61, 0.33 and 0.05, respectively.

Table I shows a summary of the classification results. The percentage of correct results was high for pedestrians not in a group, in 2-people groups, and for people with carts. Recursive estimation (with forgetting factor in (10) $\alpha = 0.05$) gave a better classification rate than single instant estimates, even though the difference was not large.

The accuracy of classifying 3-people groups was lower. This was not completely unexpected, since they were not explicitly modelled but instead we used the model for 2-people groups also for them. As shown in [7], 3-people groups tend to walk in a V-shaped formation and the spatial relations between two adjacent pedestrians in a 3-people group are typically somewhat different than for 2-people groups. In particular, the angle θ is different and can often fall out of the range typical for 2-people groups, which is why the classification frequently failed (in almost all error cases the pedestrians were classified as not being in a group).

An example of a successful estimation of group membership is shown in Fig. 3. The trajectories of the two pedestrians that were walking along the corridor (from right to left) are shown in Fig. 3a, and the corresponding estimated probabilities of non-group and group membership using both the instantaneous and recursive method are shown in Figs. 3b and 3c, respectively (the probability for being a cart-group stayed almost 0 all the time so it was omitted to keep the figure simple). The probability for being in a group was high at almost all instances resulting in correct classification.

At the end of the analysed trajectory the pedestrians slightly changed the direction of movement which affected the spatial formation and temporarily lowered the probability of being a group. Since it went below 50% and became smaller than the probability for non-group, the pair was misclassified as non-group for a few steps. This did not happen when using the recursive Bayesian estimator, which kept the group membership probability above 50%. This shows how the memory of the previous probability makes the recursive estimate more resilient to this kind of transitional behaviours, which is the reason why it gave better classification results in total.

An example of a situation where the classification gave a result different from how the coder labelled a group is shown in Fig. 4. Here again we had a group of two pedestrians walking along the corridor (from left to right). However after a while they suddenly stopped and started moving in the perpendicular direction (up) towards a store. The results in Figs. 4b and 4c show that although they were classified as group at the beginning of the trajectory, after changing the direction of movement they were classified as no longer being a group. The reason is that, as can be seen in the figure, they did not walk in an abreast formation any more but one of them was following the other, resulting in a larger angle θ. Arguably, because of that they should no longer be considered a socially interacting group, so the estimated probabilities were actually correctly updated. Since the coder only labelled whole trajectories, cases like this where pedestrians were part of the time in a group and part of the time not necessarily lead to discrepancies between the estimate and the label and is one reason why 100% classification rates cannot be obtained.

VI. CONCLUSION AND FUTURE WORK

In this work we presented the modelling of spatial formation of groups of pedestrians and a method for using this model for detecting pedestrians who are part of a group. The method allows us to estimate the probability that a pair of pedestrians form a group (or part of group) based on the observed spatial and dynamical relationship between them and to continuously update this estimate. The results show that the proposed method allows to accurately distinguish between group and non-group pedestrian pairs, as well as a person with a wheelchair or cart.

The results presented here are still preliminary and there are several areas of possible improvement. First, we did not attempt to deal with groups of 3 or more people in a straightforward manner, but only looked at the pairs of pedestrians inside the group. While this allowed us to obtain a fairly simple method, it ignored the fact that in 3-people groups the spatial relationships are somewhat different. As a result the classification did not work so well. This could be improved by either including the pairs inside larger groups in the learning of the model or by making a more complex model which directly uses the statistics for 3 pedestrians.

The method was tested on only one environment and it still needs to be tried in other environments as well. It would also be interesting to test if a single model can be found that works well across many environments. Moreover, one could apply the knowledge on the

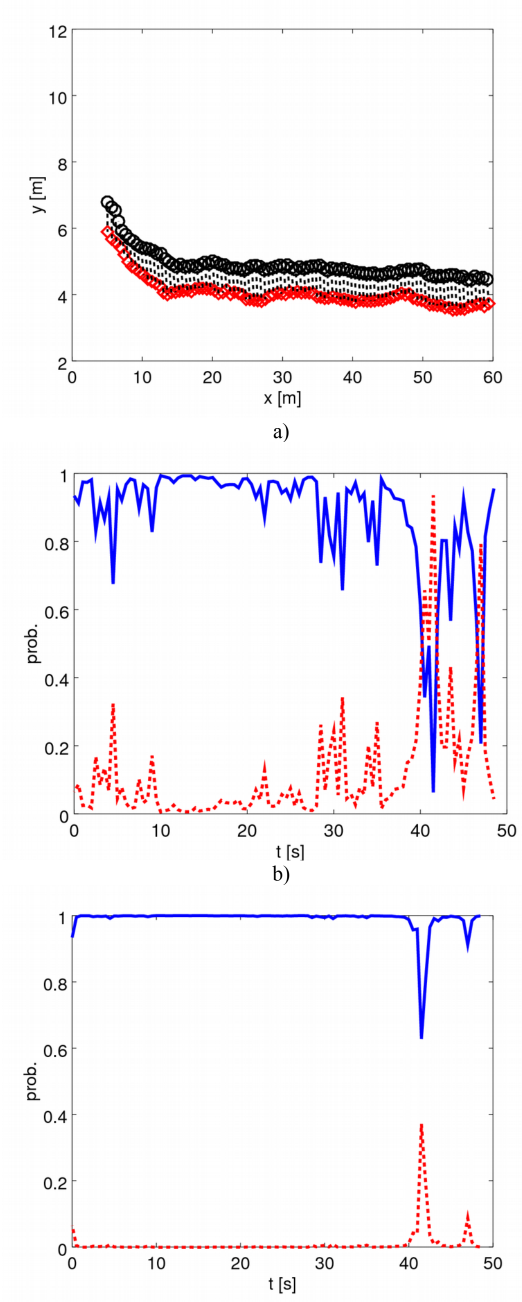

Figure 3. Example of group estimation: a) trajectories of the people in the group; b) estimation result using instantaneous estimation; c) estimation result using recursive estimation. (probabilities: ‘group’ - blue solid line; ‘non-group’ - red dashed line)

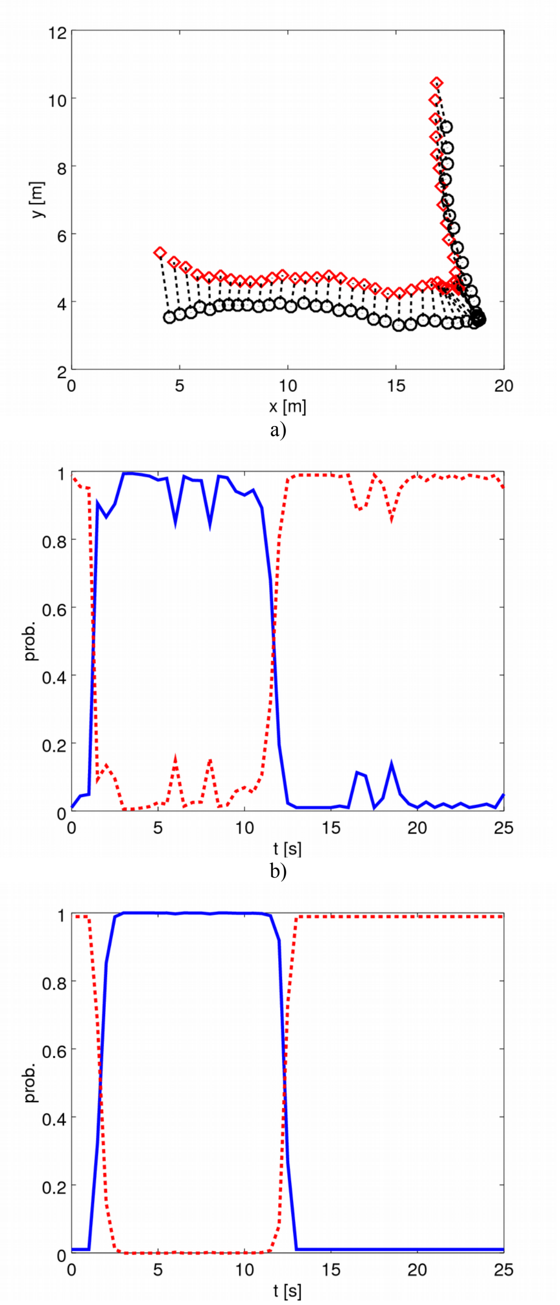

Figure 4. Example of dynamical re-estimation of group membership: a) trajectories of the people in the group; b) estimation result using instantaneous estimation; c) estimation result using recursive estimation. (probabilities: ‘group’ - blue solid line; ‘non-group’ - red dashed line)

dependence of conditions such as people density, which were studied e.g. in [22-24], to automatically adapt the model (i.e. the conditional probability densities like the ones in Fig. 2) to a specific environment and current conditions.

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