Proceedings of the 9th International Conference on Pedestrian and Evacuation Dynamics (PED2018)
Lund, Sweden – August 21-23, 2018
Paper No. 007

Estimating social relation from trajectories

Zeynep Yucel [1], Francesco Zanlungo[2], Claudio Feliciani[3], Adrien Gregorj[1], Takayuki Kanda[2,4]
[1]Okayama University
Okayama, Japan
zeynep@okayama-u.ac.jp; gregorja@s.okayama-u.ac.jp
[2]ATR IRC
Kyoto, Japan
zanlungo@atr.jp
[3]University of Tokyo
Tokyo, Japan
feliciani@jamology.rcast.u-tokyo.ac.jp
[4]Kyoto University
kanda@i.kyoto-u.ac.jp

Abstract - This study focuses on social pedestrian groups in public spaces and makes an effort to identify the social relation between the group members. We particularly consider dyads having coalitional or mating relation. We derive several observables from individual and group trajectories, which are suggested to be distinctive for these two sorts of relations and propose a recognition algorithm taking these observables as features and yielding an estimation of social relation in a probabilistic manner at every sampling step. On the average, we detect coalitional relation with 87 % and mating relation with 81 % accuracy. To the best of our knowledge, this is the first study to infer social relation from joint (loco)motion patterns and we consider the detection rates to be a satisfactory considering the inherent challenge of the problem.

***Keywords*:** Dyads, interaction, pedestrian groups, recognition, social relation.

1. Introduction

Crowd has a heterogeneous structure, i.e. it may be constituted of various elements with distinct dynamics. Although autonomous agents (e.g. wheelchairs or robots) have recently started to take part in public spaces, such as stations or shopping malls, in this study we restrict ourselves to crowds constituting of only human pedestrians. In that respect, the two basic building blocks of the crowd can be regarded as (i) individuals and (ii) pedestrian groups.

In the field of pedestrian movement and evacuation dynamics, locomotion of individuals has been studied since a long time. However, the motion of pedestrian groups has started attracting attention only recently, even though they are an important and particular element of the crowd.

The importance of pedestrian groups is mainly due to the complex dynamics acting on their motion characteristics, which distinguishes them from a mere collection of (unrelated) individuals. Moreover, depending on the public space (and thus the context or the scenario), groups may constitute up to more than half of the crowd [1], which increases their significance.

Profiling of groups is important for understanding crowd level activities, for instance, for detecting stability, collectiveness or conflict [2, 3]. Moreover, resolution of social relation is crucial to increase reliability of pedestrian simulators as well as providing automatic services to pedestrians (such as assistive robots). In addition, it eliminates the need of human labeling and extends the amount of information we can get out of the (tracking) data.

2. Background

In order to understand the dynamics acting the locomotion of pedestrian groups, we need to take a closer look into the composition of these groups. Namely, several intrinsic features of the group, such as purpose, age, or gender are shown to play a crucial role in their locomotion [4]. In this study, among those intrinsic features, we choose to focus on social relation of the peers.

According to McPhail and Wohlstein, pedestrian groups are people engaged in a *social relation* to one or more pedestrians and move together toward a common goal [5]. Due to the diversity of the social situations, there is no consensus on a universal, concrete and exhaustive list of social relations. Despite, there exist several widely accepted categorizations of fundamental forms of social relation in psychology [6, 7, 8, 9]. In such social disciplines, variations of social relations are defined on various grounds such as benefit of exchange or social domain. On the other hand, in natural disciplines, and in particular in computer science, the concept of social relation is defined and interpreted in direct relation to (i) the available data for speculating on relation and (ii) particular purpose of utilizing the relation information.

Namely, in such domains, the data used in identification of social relation is visual, i.e. images or video. In relation to that, it is subject to analysis particularly in computer vision. Several applications include resolution of kinship relation [10], recognition of domain related roles, such as birthday child and guests, understanding of hierarchical relations between leader/subordinate and interpretation of different social circles such as bikers/hippies/clubbers etc [11].

In this study, we choose to focus on such social relations,
(i) which commonly occur among our particular subjects (pedestrians in a public environment),
(ii) which are typically used in both social and natural disciplines
(iii) which enable a correspondence between the approaches of social sciences and natural sciences.

From a collective point of view of the above listed considerations, the approach of Bugental is regarded to be the most convenient model in categorizing social relations [9]. Namely, Bugental proposes a domain-based approach and divides social life into five non-overlapping domains as attachment, hierarchical power, mating, reciprocity and coalitional [9]. In particular, the classes of friends, family, couples and colleagues correspond to the domains of reciprocal, attachment, mating and coalitional, respectively.

However, we note that the last domain defined by Bugental, i.e. hierarchical relation, is eliminated in this study, since it does not apply to pedestrians in a public space to the full extent. Namely, the action (i.e. locomotion) and environment (i.e. public space) impose certain conditions on possible classes of social relation, such that social relations, which are a consequent of a particular action or depend on the environment, may not occur for our specific action and in our specific environment. For instance, leader-subordinate relations as presenter-audience relationship in a seminar room or teacher-pupil relationship in a classroom cannot be observed in our case.

Furthermore, in this study, as a first step to identification of social relation from locomotion, we contain ourselves to two kinds of social relations: mating and coalitional. We examine dyadic groups, which are in one of those relations, and propose an algorithm to distinguish them using a set of observables derived from 3D range data originating from our previous works [4] and [12]. In the future, we aim expanding our scope to the relations of reciprocal and attachment.

3. Dataset

The dataset used in this study is already introduced by [13] and is freely available at [14]. In what follows, for the integrity of the manuscript, we briefly provide relevant information on the dataset but refer the interested reader to [13] and [4] for a through discussion.

The dataset is recorded in an indoor public space covering an area of approximately 900 m^2 in a one year time window. The public space is the ground floor of a business center which is connected to a train station, a ferry terminal and a shopping center. Therefore, it is populated with pedestrians coming from a diverse background.

Over the course of the data collection campaign, range information is registered for over 800 hours using 3D depth sensors. Using the algorithm of [15], pedestrians are automatically tracked and their position (on 2D floor plane) and height are computed, which can be all downloaded freely from [14]. As a result of the tracking process, the cumulative density map of the environment is found as in Fig. 1(a).

In addition to the range information, we also collected video footage for labeling purposes. Based on the video, three coders label the dataset with respect to several intrinsic group features. One specific feature refers to the apparent relation, where the possible options are friends, family, couples and colleagues, which correspond to the domains of reciprocal, attachment, mating and coalitional, respectively [9].

For confirming the inter-rater reliability of the labeling process, we adopt a particular procedure so as to minimize the work load for coders. Namely, we ask two coders to label only part of the dataset, where the third coder labels the entire dataset. Inter-rater reliability is evaluated based on the data, which is common for all coders. Using several prominent statistical measures such as Cohen's κ, Fleiss' κ and Krippendorf's α, the coders are found to be in considerable agreement [16, 17, 18, 4]. Therefore, we consider the labels of the third coder to be beyond any doubt and base our ground truth on her labels. As a result, the relation between dyads is distributed as follows: 358 coalitional, 96 mating, 216 attachment and 318 reciprocal.

In this study we are particularly interested in differentiating between coalitional and mating relations (i.e. "colleagues" and "couples"). This choice is established based on the observations presented in [4], which suggest that coalitional and mating relations present the most distinct features among all combinations of relation pairs. Namely, [4] illustrates that work-oriented dyads move with a significantly larger velocity in comparison to not work-oriented dyads (i.e. mating, attachment, reciprocity relations). On the other hand, [4] proves that the variation on distance between the peers is distributed over a range of values, where coalitional relation is associated with the largest expected value and mating relation is associated with the smallest expected value. In other words, among all relations, on the average, colleagues move with the largest distance, whereas couples move with the smallest distance between peers.

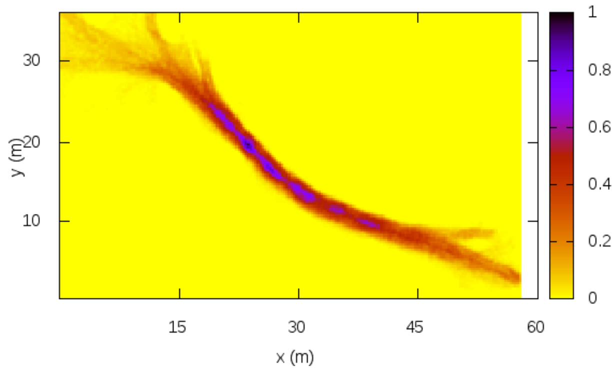
From these dyads in coalitional or mating relation, we require a minimum observation duration of 15 secs, which we regard to be sufficiently long to speculate on the social relation. Therefore, we initially consider the 358 dyads in coalitional relation and 96 dyads in mating relation.

In addition, from the trajectories of these dyads, we eliminate the portions with unexpected or irregular behavior (such as stopping and waiting or meeting, splitting etc.) using similar criteria to [13]. Specifically, we require a minimum average group velocity of 0.5 m/sec and a maximum interpersonal distance of 2 m. After eliminating the portions of trajectories, which are not inline with our requirements, we derive and contrast several observables from the remaining portions.

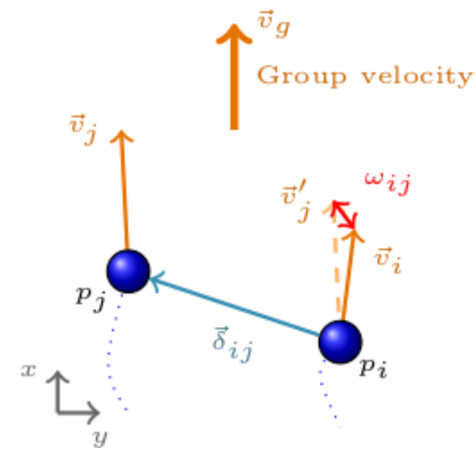
The details of the definitions of observables and the cumulative empirical observations are presented in Section-4.

4. Observables and Empirical Distributions

In examining the joint behavior, we focus on the following observables: interpersonal distance, group velocity, velocity difference and height difference of the peers. In what follows, we provide the definitions of these observables on a sample pair (p_i, p_j) depicted in Fig. 1(b).



(a)



(b)

Fig. 1: (a) Cumulative density map of the environment and (b) The observables depicted on a sample dyad .

4.1. Definition of Observables

The observables are computed on a normalized frame of reference. Namely, we rotate the reference frame such that the x-axis corresponds to the motion direction of the group. The advantage of this transformation is that it enables processing of the groups, which move along different (e.g. opposite) directions or change their motion direction (e.g. by taking a curve).

The observables depicted in Fig. 1(b) are defined explicitly as follows:

(i) Interpersonal distance $\delta_{ij} = \sqrt{(\delta^2_{x(i,j)} + \delta^2_{y(i,j)})}$

(ii) Group velocity $v_{g(i,j)} = \left| (\overrightarrow{v}_i + \overrightarrow{v}_j)/2 \right|$

(iii) Velocity difference of the peers $\omega_{ij} = \left| \overrightarrow{v_i} - \overrightarrow{v_j} \right|$

(iv) Height difference of the peers $\Delta\eta_{(i,j)} = \left| \eta_i - \eta_j \right|$, where η_i and η_j stand for the height of p_i and p_j, respectively.

Henceforth, we drop the indices for the simplicity of notation.

4.2. Empirical Distributions of the Observables

The cumulative distribution of interpersonal distance δ, relating the entire set of dyads in coalitional and mating relation is presented in Fig. 2(a). It is clear that mating dyads stay in closer proximity than coalitional dyads and are more stable in their behavior. In other words, in Fig. 2(a), the values regarding mating dyads are distributed around a smaller mean and with a lower deviation.

Moreover, we take a closer look into on the projections of interpersonal distance along and perpendicular to motion direction [4]. Namely, we denote the projections of δ_{ij} on x-axis and y-axis with δ_x and δ_y, respectively (see Figure1-(b)). Here, δ_x corresponds to the *depth* of the group, whereas δ_y corresponds the *abreast distance* of the peers. Between, collisional and mating dyads, group depth δ_x is found to have no

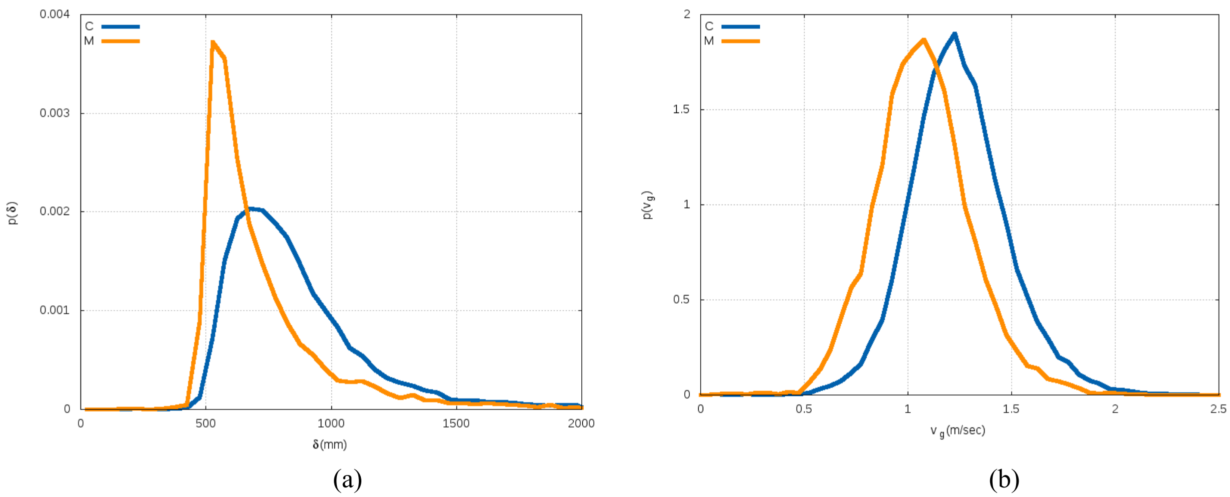


Fig. 2: Empirical distribution of (a) interpersonal distance and (b) group velocity in coalitional (C) and mating (M) relation.

significant difference; but abreast distance δ_y and δ are found to present basically the same characteristics. Therefore, our choice of interpersonal distance is regarded to embrace the prominent representations of proxemics.

As presented in Fig. 2(b), group velocity v_g of the mating dyads is lower than that of the coalitional groups. Moreover, despite being less clear than the distinction of group velocity, also the absolute difference of velocities ω is found to be different between two social relations as shown in Fig. 3(a) due to the lower mean and heavier tail.

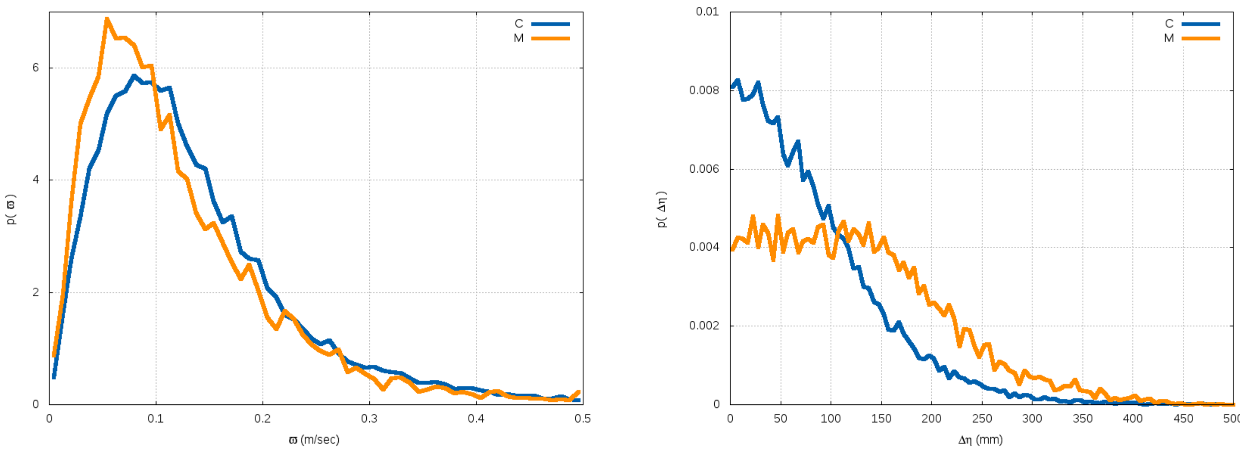
The last observable of interest, height difference of the peers, $\Delta\eta$, depicted in Fig. 3(b), does not depend on the motion of the peers but rather on their gender in an indirect way. Namely, mating relationship often refers to a heterosexual pair, whereas it is not uncommon for coalitional groups to be composed of same gender peers. In this respect, height difference turns out to be a discriminating feature, since it is higher for mating relation than for coalitional relation.

Here we would like to point out to one certain advantage of using height difference instead of height. Height of individuals may vary from one society to another due to genetic factors [19], whereas height difference between male and female is universally more stable. Therefore, using $\Delta\eta$ instead of η makes the method more flexible and generalizable over different societies.

In addition to these subjective evaluations, we carry out an ANOVA to confirm the inferences mentioned above. All observables of δ, v_g, ω, and $\Delta\eta$, are found to have a p-value smaller than 10^{-4}. Adopting the widely accepted threshold value of 0.05 for statistical significance [20], we can say that there exists a considerable distinction between coalitional and mating relation in terms of all observables.

5. Recognition of Social Relation

In this section, we describe our method for discriminating coalitional and mating relations using the observables introduced in Section 4. Specifically, we take a Bayesian stand-point similar to [21] and



(a) (b)

Fig. 3: Empirical distribution of (a) velocity difference (b) height difference of peers for dyads in coalitional (C) and mating (M) relation.

compute the conditional probability that a given set of observations come from a dyad in a particular social relation.

Suppose that from a pair of pedestrians (p_i, p_j) we gather a set of observations at time t and denote it by $\Sigma(t) = \left\{ \delta(t), v_g(t), \omega, \Delta\eta \right\}$.

Let us denote their social relation by r, where the possible values of r are coalitional C and mating M. We compute the probability that the observation set Σ, gathered at time t, comes from a dyad in social relation of r, $P_t(r \,|\, \Sigma)$, as follows,

$$P_t(r \,|\, \Sigma) = \frac{P_t(\Sigma \,|\, r) P_t(r)}{P_t(\Sigma)} \tag{1}$$

Here, $P_t(r \,|\, \Sigma)$ is the posterior probability that the dyad comes from relation r given the observation set Σ. In addition, $P_t(\Sigma \,|\, r)$ is the likelihood term and $P_t(r)$ is the prior probability of social relation.

While computing the likelihood, we assume that the four kinds of observables $\Sigma(t) = \left\{ \delta(t), v_g(t), \omega, \Delta\eta \right\}$ are independent.

This assumption enables expressing the likelihood term using the following product,

$$P_t(\Sigma \,|\, r) = P_t(\delta \,|\, r) P_t(v_g \,|\, r) P_t(\omega \,|\, r) P_t(\eta_s \,|\, r) \tag{2}$$

For each conditional probability in Eq. 2, we use the empirical distributions. Namely, we shuffle the dataset and randomly select a subset of the pairs to build the probability density functions.

As for an initial value for our prior belief, $P_0(r)$, we adopt an equal probability to avoid any bias. Thus,

$$P_0(r) = (0.5 \quad 0.5), \tag{3}$$

since we have two possible cases for social relation.

As time elapses, we propose updating (or not) the prior as in Eq. 4, where the parameter α defines the rate of update.

$$P_t(r) = \alpha P_0(r) + (1 - \alpha) P_{t-1}(r). \tag{4}$$

Regarding the update, we contrast three cases as follows:

(i) Update priors to the last computed value (i.e. the posterior) at every step.
(ii) Update priors using a linear combination of the initial value and last computed probability value
(iii) No update on the priors

The 3 cases described above can be realized using $\alpha = \{0, 0.5, 1\}$, respectively.

The term, $P_t(\Sigma)$, which is called the marginal likelihood, is not necessary to be explicitly computed. Specifically, we make use of the fact that a particular pair comes either from a C or M relation and thus the sum of the posterior probabilities, which are scaled by the same term in Eq. 1, need to sum up to 1.

6. Results

In practice, we randomly choose $30\,\%$ of the pairs and use their trajectories to build the probability density functions in Eq. 2. The remaining $70\,\%$ are used to test our estimation method. Moreover, repeating this validation procedure 20 times, we compute the mean and standard deviations of performance values to investigate the sensitivity (i.e. dependence) of the observables on training set. By randomly picking $30\,\%$ of the entire samples and repeating this procedure 20 times, the probability that a particular sample is not used for training falls below 10^{-3}.

From, the recognition rates are presented in Table-1, it is observed that coalitional relation is recognized with a somewhat higher rate for all values of α, which could be due to the imbalance of samples in the dataset as given in Section-3. Moreover, taking a fixed and unbiased prior performs slightly better than applying an update. In addition, the effect of random shuffling is regarded to be minute, which suggests that the observables are stable across samples and the method is resilient to changes in training set. All in all, the proposed method achieves significant accuracy considering the challenge of the problem.

Table 1: Recognition performance (%) for varying α.

α	C	M
0	88.5 ± 2.1	73.4 ± 5.0
0.5	88.1 ± 2.1	79.1 ± 3.8
1	87.1 ± 2.3	81.3 ± 4.1

7. Conclusions

This study describes a method to identify social relation between members of a pedestrian group. We particularly focus on dyadic groups belonging to a coalitional or mating relation. Several observables are derived from individual and group trajectories in addition to height difference of the peers. A recognition algorithm, which uses these data as features, is proposed. Running it over the entire course of the trajectory updating the estimation of social relation in a probabilistic manner at every sampling step, recognition rates are computed. On the average, coalitional relation is detected with $87\,\%$ and mating relation with $81\,\%$ accuracy, when the prior is not updated. We believe this is the first study to recognize social relation from trajectory and height information.

Acknowledgements
This work was partially supported by JST-Mirai Program Grant Number JPMJMI17D4, Japan. This paper is based on results obtained from a project commissioned by the New Energy and Industrial Technology Development Organization (NEDO).

References

1. M. Schultz, L. Rößger, H. Fricke, and B. Schlag, “Group dynamic behavior and psychometric profiles as substantial driver for pedestrian dynamics,” in Pedestrian and Evacuation Dynamics 2012, pp. 1097– 1111, Springer, 2014.
2. C. von Krüchten, A. Schadschneider, “Empirical study on social groups in pedestrian evacuation dynamics,” Phys A: Stat Mech Appl. 2017;475:129–141.
3. J. Shao, C Change Loy, X Wang, “Scene-independent group profiling in crowd,” In: CVPR. Columbus, OH; 2014. p. 2219–2226.
4. F. Zanlungo, Z. Yücel, D. Brscic, T. Kanda, and N. Hagita, “Intrinsic group behaviour: dependence of pedestrian dyad dynamics on principal social and personal features,” arXiv preprint arXiv: 1703.02672, 2017.
5. C. McPhail, R. Wohlstein, “Using film to analyze pedestrian behavior,” Sociological Methods & Research 1982;10:347–375.
6. A. P. Fiske, “The four elementary forms of sociality: framework for a unified theory of social relations.,” Psychological review , vol. 99, no. 4, p. 689, 1992.
7. M. S. Clark and J. Mills, “Interpersonal attraction in exchange and communal relationships.,” Journal of personality and social psychology , vol. 37, no. 1, p. 12, 1979.
8. E. B. Foa and U. G. Foa, “Resource theory,” in Social exchange , pp. 77-94, Springer, 1980.
9. D. B. Bugental, “Acquisition of the algorithms of social life: A domain-based approach.,” Psychological bulletin , vol. 126, no. 2, p. 187, 2000.
10. V. Ramanathan, B. Yao, L. Fei-Fei, “Social role discovery in human events,” CVPR 201, pp. 2475-2482, IEEE.
11. G. Wang, A. Gallagher, J. Luo, D. Forsyth, D. , “Seeing people in social context: Recognizing people and social relationships,” ECCV 2010, pp. 169-182, Springer.
12. Z. Yücel, F. Zanlungo, T. Ikeda, et al. “Deciphering the crowd: modeling and identification of pedestrian group motion,” Sensors. 2013;13(1):875– 897.
13. F. Zanlungo, D. Brščić, and T. Kanda, “Spatial-size scaling of pedestrian groups under growing density conditions,” Physical Review E, vol. 91, no. 6, p. 062810, 2015.
14. ATR-IRC, “Dataset: Pedestrian tracking with group annotations,” http://www.irc.atr.jp/sets/groups/ , (accessed January, 2018).
15. D. Brscic, T. Kanda, T. Ikeda, and T. Miyashita, “Person tracking in large public spaces using 3-d range sensors,” IEEE Transactions on Human-Machine Systems , vol. 43, no. 6, pp. 522-534, 2013.
16. Cohen, Jacob. “A coefficient of agreement for nominal scales.” Educational and psychological measurement 20.1 (1960): 37-46.
17. Fleiss, Joseph L. “Measuring nominal scale agreement among many raters.” Psychological bulletin 76.5 (1971): 378.
18. Krippendorff, Klaus. “Reliability in content analysis.” Human communication research 30.3 (2004): 411-433.
19. Ministry of Education, Culture, Sports, Science and Technology, “Official Health Statistics Survey,” http://www.mext.go.jp/component/b_menu/other/__icsFiles/afieldfile/2014/03/28/1345147_1.pdf , (accessed January, 2018).
20. Goodman, Steven N., and Jesse A. Berlin. “The use of predicted confidence intervals when planning experiments and the misuse of power when interpreting results.” Annals of internal medicine 121.3 (1994): 200-206.
21. D. Brščić, F. Zanlungo, and Takayuki Kanda. "Modelling of pedestrian groups and application to group recognition." Information and Communication Technology, Electronics and Microelectronics (MIPRO), 2017 40th International Convention on. IEEE, 2017.