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APPLYING QUALITATIVE TRAJECTORY CALCULUS TO HUMAN MOTION FNFLYSIS: A CASE STUDY TOWARDS ROBOT SOCIAL PATH PLANNING

ABSTRACT

Qualitative Trajectory Calculus (QTC) offers a powerful set of tools towards selectable-granularity abstraction of relative trajectories of moving entities, while preserving essential aspects of their interaction. In this paper, we present a case study of an application of QTC towards analyzing human motion and interaction patterns in a shopping mall. The ultimate purpose of this study is to use the derived results towards tuning human-aware social path planning algorithms for robots cohabitating and interacting with humans in malls, and in other public spaces. This is increasingly important given the rapid rise of service robots and the need for human-aware navigation which maximizes the safety and comfort of humans while preserving social norms such as proxemics and personal spaces.

KEYWORDS

Qualitative Trajectory Calculus; Human-aware navigation; Crowd flow datasets and analysis; Qualitative Representations; Robot motion planning.

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ПРИМЕНЕНИЕ QUALITATIVE TRAJECTORY CALCULUS ДЛЯ АНАЛИЗА ДВИЖЕНИЯ ЛЮДЕЙ: СОЦИАЛЬНО-ОРИЕНТИРОВАННОЕ ПЛАНИРОВАНИЕ МАРШРУТА ДЛЯ РОБОТОВ

АННОТАЦИЯ

Qualitative Trajectory Calculus (QTC) представляет собой мощный набор инструментов для описания взаимосвязанных траекторий движущихся объектов с необходимым уровнем абстракции, сохраняя при этом основные аспекты их взаимодействия. В этой статье мы представляем рассмотрение конкретного примера применения QTC для анализа движения и взаимодействия людей в японском торговом центре. Конечная цель данного исследования заключается в использовании полученных результатов для улучшения алгоритмов социально-ориентированного, учитывающего психологию людей планирования пути для мобильных роботов, функционирующих и взаимодействующих с людьми в зданиях торговых центров, а также в других подобных помещениях. Это становится все более важным, учитывая быстрый рост сервисной робототехники и потребность в навигации, повышающей безопасность и комфорт людей, соблюдая при этом социальные нормы, такие как проксемика и личное пространство.

КЛЮЧЕВЫЕ СЛОВА

Qualitative Trajectory Calculus; Навигация, учитывающая психологию людей; Анализ движения потока толпы по набору данных; Качественное представление данных; Планирование маршрута для робота.

INTRODUCTION

Qualitative Representations often offer several advantages in comparison to their quantitative continuous counterparts, in specific domains of application. Such a case is Qualitative Trajectory Calculus (QTC) [1], which was created by Nico Van De Weghe in 2005. It offers a powerful set of tools towards selectable-granularity abstraction of relative trajectories of moving entities, while preserving essential aspects of their interaction. It has been used in the past towards proving encodings of relative trajectories which can easily utilised towards analysing aspects of interactions, or even synthesising interactions [2] that maintain required essential properties, in a range of diverse domains: from bird flights [3] to human-robot interaction [4] and beyond. Furthermore, a promising domain for wider application of QTC is human motion analysis, for example in sports [5], [6], either across body parts of across players.

Recently, robots are starting to become an important part of our everyday life, and very soon it is predicted that people will regularly be interacting with robots at work, at home and in public places. Due to the increasing co-habitation of spaces by humans as well as robots, though, robot motions should take into account human safety as well as human comfort, and should also conform to implicit social rules regarding interaction and space sharing. The psychological field of proxemics [7], [8], provides information on many such considerations, and recently there is an increasing amount of literature dealing explicitly with human-aware navigation for robots [9], [10] as well as more specifically with the problem of social path-planning [11], [12]: specialized robot path planning, aiming towards motion as well as interaction with single humans and groups of humans, that takes into account psychological considerations.

Towards tuning the parameters of social path planning and other human-aware navigation algorithms, empirical observations of human-human interactions can be informative. For that purpose, and aiming in particular to introducing human-aware robots in crowded large shopping mall areas, we decided to study human motions and interactions for the case of a mall in japan, utilising the ATC dataset [13], and choosing Qualitative Trajectory Calculus as our main representational framework. At a further stage, we plan to use the results of our human data analysis, towards empirically-informed and parametrically-tuned human-robot interaction synthesis, utilizing QTC as well as quantitative parameters derived from our studies.

Thus, in this paper we are presenting a methodology as well as initial results from the first stages of analysis of the ATC dataset using QTC, towards creating robots that can path plan and behave in manners which maximize human comfort and which are natural when it comes to human proxemics norms and expectations. We will start our exposition by providing appropriate background in relevant topics and on QTC. Then, we will introduce the data set, and proceed with the steps of our analysis and the derived results. Finally, we will discuss future steps and provide a concise forward-looking conclusion.

BACKGROUND

A. Qualitative Representations

The relative inaccuracy of qualitative representations can naively be considered as a disadvantage as compared to full quantitative information. However, in many cases qualitative representations are not only more efficient that full quantitative ones, but are also successful at throwing away unnecessary details while keeping the essential information for the task at hand. Human cognition heavily relies on qualitative information, for example when it comes to spatiotemporal descriptions and reasoning.

Three main principals of modern qualitative modeling, as summarized in [14], are:

- Discretization
- Relevance
- Ambiguity

Full-accuracy crisp continuous-valued representations are not only practically infeasible, even for the case of floating-point digitization, but also usually hide unrealistic assumptions about measurement accuracy and absence of noise, and are computationally highly expensive. Therefore, different, and even better, adjustable levels of discretization and symbolification often provide great advantage. Furthermore, qualitative representations are usually fine-tuned to specific purposes or tasks; and thus their relevance is of high importance. Finally, qualitative representations can often inherently handle varying levels of ambiguity and incomplete knowledge, which in many cases is highly advantageous.

For instance, one can think of the three symbols “+”, “-“, “0” as a very simple qualitative representation for the real numbers [15]. One can also introduce thresholds and ordering, and thus say that some physical quantity is “below “, ”above”, or “equal” to some predetermined threshold, or one can even move towards derivatives and rates of change and say that it is “increasing”, “decreasing”, “stable”. A similar three triplet-symbol system covering values, velocities, and accelerations, is used for example at the core of [16], towards qualitatively representing human activities, while also being augmented with discretized quantitative information. Furthermore, qualitative dynamics and qualitative reasoning and simulation [17] has successfully been applied to a variety of domains in the past.

B. Human-Aware Robot Navigation

Service robotics is growing briskly and is expected to continue to grow even faster in the nearest future [18]. Consequently, robots and people will interact with each other in different environments such as public places, home and work (for example, [19]-[24]) more often. This means that robots and humans will be engage in implicit and explicit interaction more frequently. *Explicit* interactions include robots approaching humans and vice-versa towards interacting, human following robots and vice-versa, as well as walking side by side. *Implicit* interactions include movements aiming towards the minimization of the possibility of encounter, active collision avoidance, staying in line with people etc. All those spatial interactions of robots with people should be performed effectively and at the same time generate minimal discomfort for humans. Thus, of high relevance are also the rules studied in the psychological field of proxemics [25], [26], [27], as well as other social rules. Furthermore, robots should take into account human comfort while they are engaged in productive interaction. These are the main goals of human-aware navigation. It is a relatively new field of robotics at the intersection of *human-robot interaction* (HRI) and motion planning. While motion planning is a fairly mature field of robotics ([28],[29]), and active algorithmic development started in the 80's [30], HRI is a relatively newer area of research, becoming established in the previous decade. However, the HRI field contains many aspects as well as settings of interaction, going beyond the purely spatial, and including verbal, non-verbal, gestural, as well as short-term, long-term, and much more. Consequently, human-aware navigation is connected to HRI and is also related to relevant psychological sub-fields as well as the social sciences.

C. Crowd flow datasets and analysis

Recently systems such as video-surveillance systems [31] and laser-based tracking systems [32] are becoming widespread in public places, and often operate either manually, or semi-autonomously. Such systems can be beneficial in multiple ways, beyond increasing safety. For example, information about the spatiotemporal patterns of crowd flows could help decongest passageways and enable targeted positioning of shops in a shopping mall. Such systems can also be used for the needs of intelligent responsive environments, and the data derived are also invaluable towards beter mathematical models of crowds [33]. Due to all of the above reasons, a number of crowd flow datasets have become available in the public domain: some in the form of pure raw data, others with some basic analysis results attached, such as in the case of [34], [13]. Availability of such datasets also gives an opportunity for examining motions of individual persons and analysis of the behaviors of small groups, which arise within, and are embedded in the larger crowds.

D. Qualitative Trajectory Calculus

QTC was first introduced by Van de Weghe as a method of qualitative representation of relative trajectories of moving objects. The original QTC formulation was two-dimensional, and was later expanded to three dimensions [3]. There exist two variations of it based on the time dimension: continuous-time QTC and a discrete-time QTC. A brief description of the meaning of the original QTC symbols is given in table [Table 1].

Table 1. Original QTC symbols meaning [2]

	Name of constraint	-	+	0
A	Distance for object k	k is approaching l	k is moving further away from l	distance remains steady
B	Distance for object l	l is approaching k	l is moving further away from k	distance remains steady
C	Speed & k is slower than l	k is slower than l	k is faster than l	move with the same speed
D	Side for object k with respect to line kl:	k is moving to the left of the line	k is moving to the right of the line	k moves along the line
E	Side for object l with respect to line kl	l is moving to the left of the line	l is moving to the right of the line	l moves along the line
F	Angle (defining as θ1 the minimal angle between the velocity vector of k and vector kl and θ2 the equivalent for l)	$\theta 1 < \theta 2$	$\theta 1 > \theta 2$	otherwise

<u>THE DATASETS</u>

In our work we have used a dataset of people movements taking place in part of a big shopping and business center Asia and Pacific Trade Center in Osaka, Japan [34], [13]. This dataset was taken in part of the building - corridor and hall. The tracking area and sensor locations are shown in the figure 1.

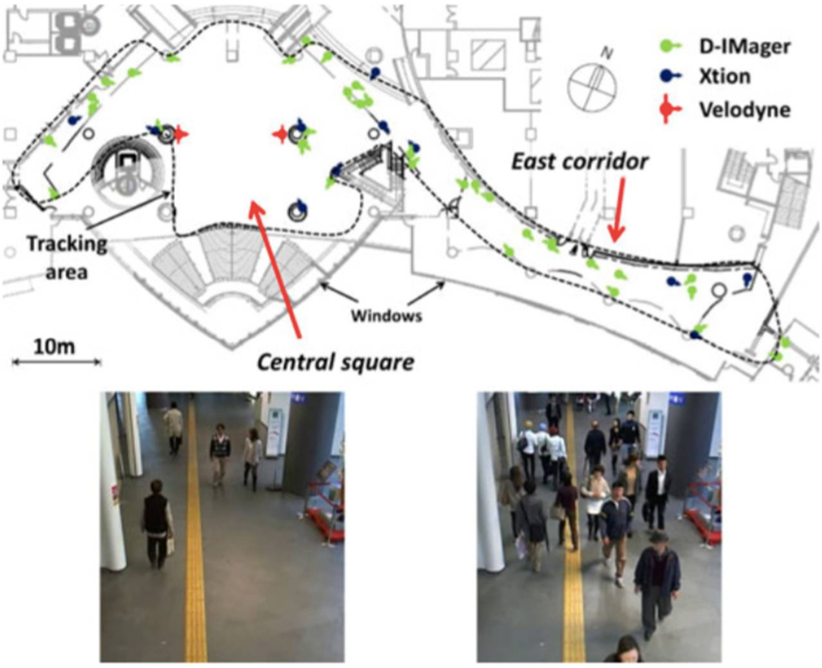

Figure 1. Tracking area and sensor setup in ATC shopping mall. The dashed line shows the border of the area covered by the sensors. The photos below show the corridor area in the afternoon on a typical weekday (left) and weekend (right) [32]

This dataset contains individual pedestrian as well as group data. Individual pedestrian information was obtained by using automatic tracking systems. The system consists of multiple different 3D range sensors and covering an area of about 900 m^2. Group information is kept in a different file. It was obtained by manual labeling according to synchronized information from video-cameras located in the observed area.

The ATC dataset contains 6 days of experiments. For each day the data for 4 one-hour periods are provided: 10:00-11:00, 12:00-13:00, 15:00-16:00, 19:00-20:00. Person tracking files contain the data for all persons that were tracked in the environment on a given day and period of time. Each row corresponds to a single tracked person at a single instant of time. The following fields were used:

TIME [s] (unixtime + milliseconds/1000), PEDESTRIAN_ID, POSITION_X [mm], POSITION_Y [mm]

Group files contain the group annotations for the given day. In our initial experiments, we have used following information only about pairs (not more than 2 people):

PEDESTRIAN_ID, PARTNER_ID

TRAJECTORY DATA PROCESSING

The methodology that we are utilizing consists of two main stages: quantitative analysis, followed by qualitative. During the **quantitative** stage, we examine the probabilistic distributions of a number of quantities: trajectory durations, velocities, number of stopping events (stasis), durations of stopping events, as well as spatial aspects: distribution of stops, entry and exit points, etc. During the **qualitative** stage, we examine the symbol sequences that are arise from pairs of trajectories, and especially focus on the types of relations between trajectories that might arise, such as leader-follower relations vs. uncorellated motion, moves to approach or detach from interaction etc. Our goal is to later use the information obtained can be used for tuning robot motions, but it could also be used for other purposes, such as optimizing building design, shop placement, etc.

Let us start with the initial quantitative phase. First, we examined the ***duration of the trajectories*** contained in our dataset. We initially examined *short trajectories* with duration less than 10 seconds. We observed that most of these trajectories were located on the borders of tracking area. In most cases (type-0) they represent humans that just for a short time entered the scanned area but did not walk through. In a few cases these trajectories were just a noise of automatic tracking systems (type-1). Due to the non-interesting (for our purposes) nature of these two types of trajectories, we filtered them from our dataset (731 remained out of 1090 for 10am-11am, and 2226 out 3138 for 12-1pm). The statistics of the duration for all the remaining trajectories for two hours of the first day are illustrated in figure 2.

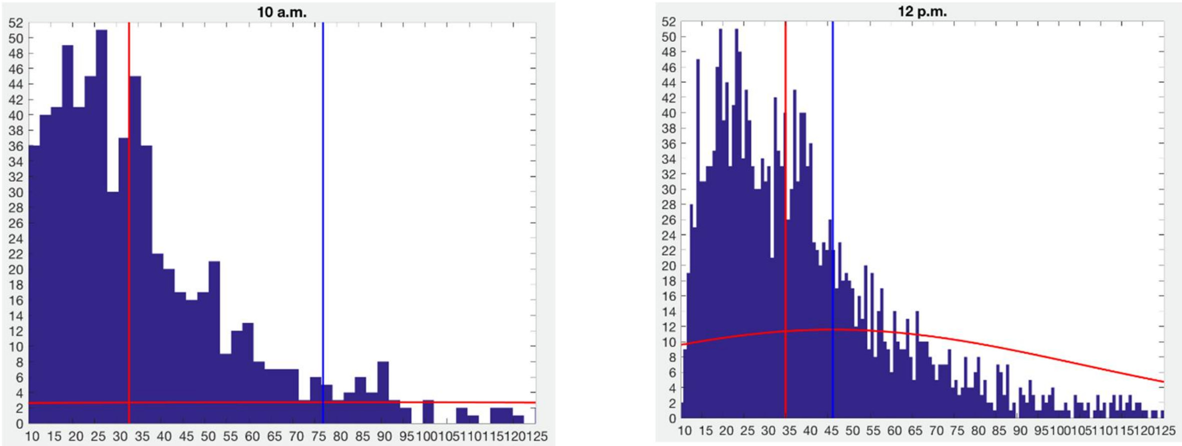

Figure 2. Durations of trajectories during the 10am-11am and 12am-1pm of the first day of the dataset (seconds) [34] (median~33)

This histogram represents trajectory durations for people captured by the tracking system. The red vertical line represents the median, while the blue vertical line represents the mean value.

Next, we started examining ***velocity statistics***. Actually, velocities for any moment of the tracking process are pre-calculated and given explicitly in the data files of the original ATC dataset. However, the distribution of the pre-calculated velocities is close to normal (figure 3). This seems to be contrary to intuition, given that we observed that many people in the dataset were stopping (or having very little motion) for extended time intervals. This naturally should have led to a bimodal distribution: with one peak near the average walking speed of the person, and the other peak near the average velocity of the apparent micro-motions when the person is stopped. We thus recomputed velocities using the trajectory positions data. The distribution that we got looks as we expected – it is bimodal. That means that we can now also use it towards *discriminating time periods when the person moves from those when the person stops*, using an adaptive dynamical threshold. This distribution for the period of time from 12am to 1pm of the first day is shown in figure 3. All further figures in this paper will from now on represent statistics for this specific time period, chosen for the purpose of illustration. The same methods can be used for the other periods.

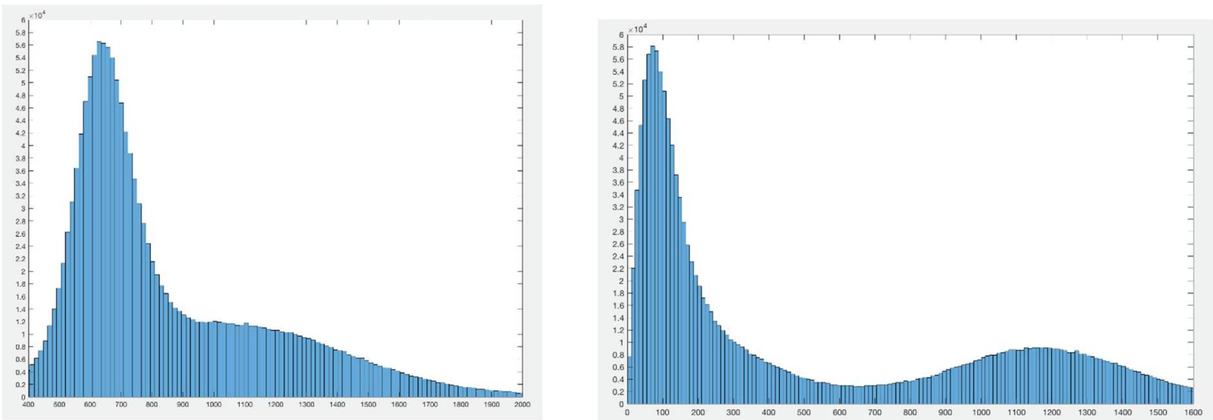
Figure 3. Distribution of velocities using given values for all people during the first day from the dataset (on the left). Distribution of velocities using computed values for all people during the first day from the dataset (on the right: bimodal distribution – average speed while stopped approx. 100 mm/sec, average speed when walking 1170 mm/sec (~4.5km/hr) , approx. threshold 650mm/sec)

Stopping statistics are presented on figures 4-8. We start by examining the ***number of stops per trajectory***: Trajectories that have no stops don't appear in this figures (706 trajectories have at least one stop, out of 2226 – i.e. ~32%). Out of the 706 trajectories that have at least one stop, 302 have one stop only (~43%), 165 have two stops only (~23%), and so on, as can be seen in Figure 4. The number of stops on a log-log plot reveals an approximate fit to a $1/x^n$ law. Notice that for most people (~94%) there is no more then 4 stops total per trajectory and that many people are crossing the area without stops at all (~68%).

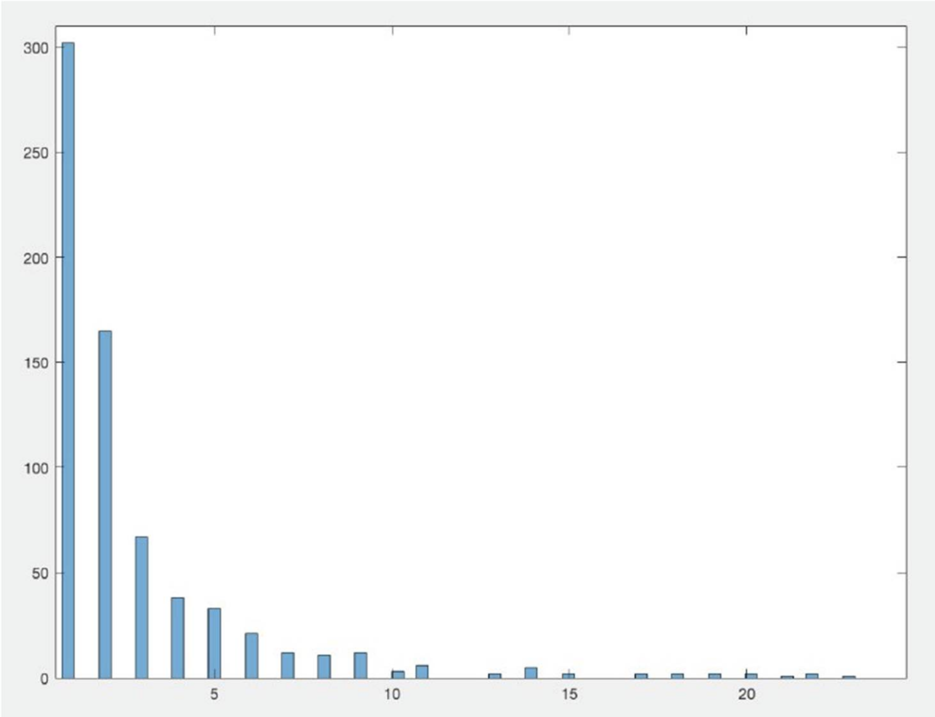

Figure 4. Histogram of numbers of stops per trajectory for one hour of the dataset (302 with 1 stop, 165 with 2 stops etc)

Following the number of stops per trajectory, we then examine the ***stop duration statistics***. Looking back into figure 2, the median trajectory duration was roughly 33sec, with a much higher mean (45sec-75sec), due to the outliers: some very long trajectories. However, for those trajectories that had stops, the sum duration of the stops, had a median of 15sec (figure 5); i.e. almost half of the total time. Indeed, in figure 7 one can see the distribution of this ratio: median 41% stasis (59% walking). Given that more than one stops often occur, the median duration of a single stop is 6sec.

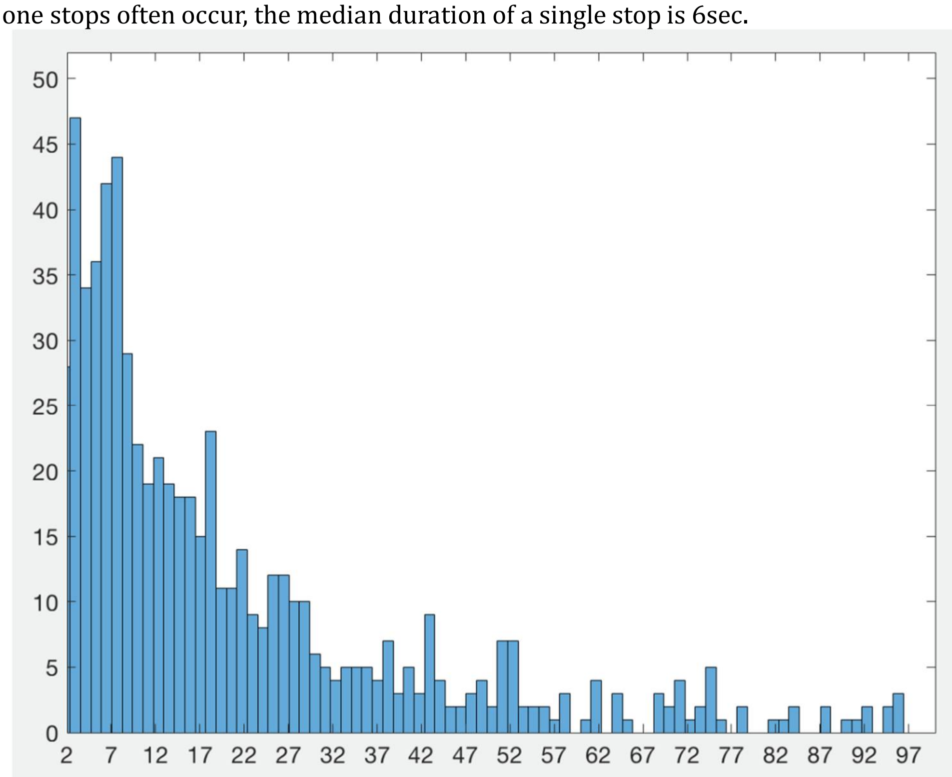

Figure 5 Sum Duration of all Stops in one Trajectory (mean ~ 36s, median ~ 15s)

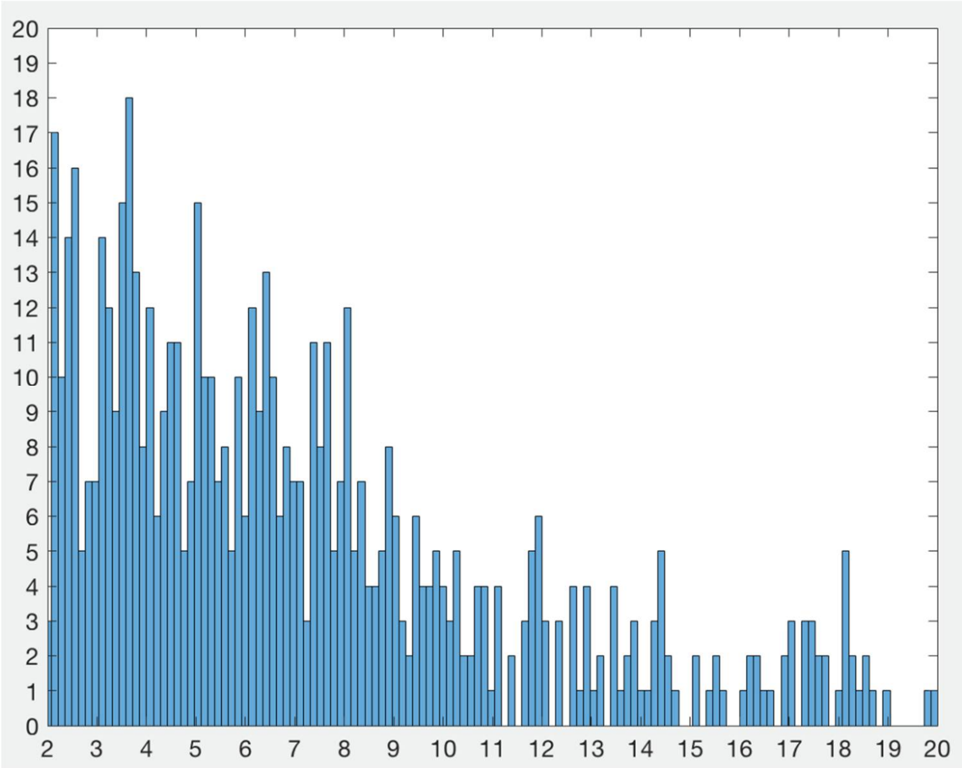

Figure 6. Mean Duration of Stops per trajectory (mean ~ 12s, median ~ 6s)

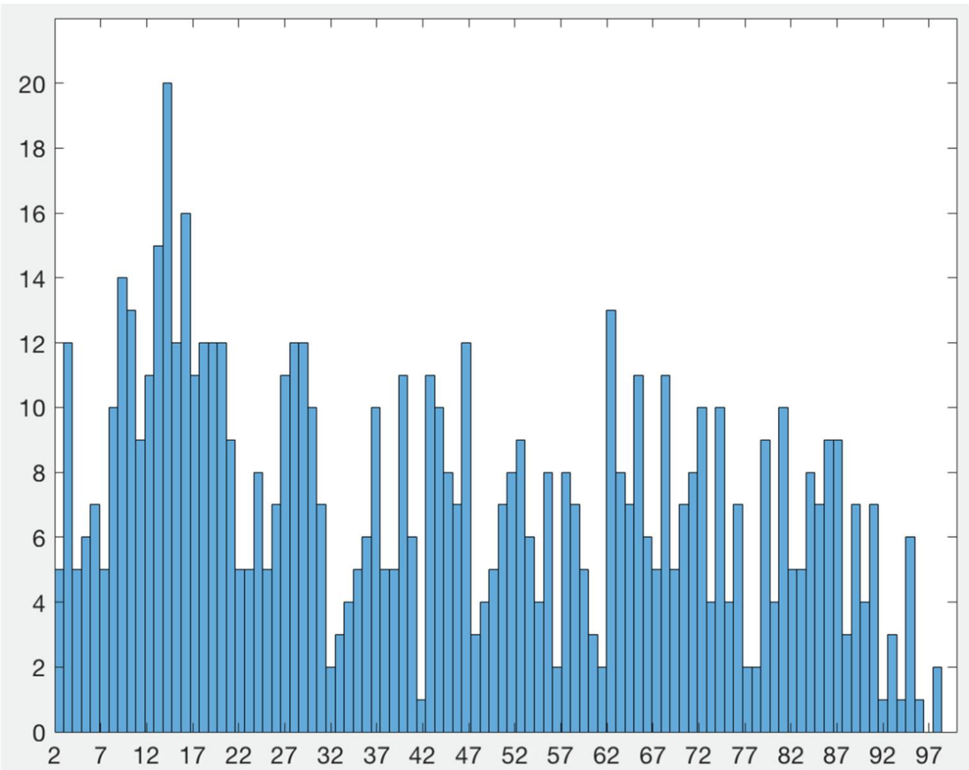

Figure 7. % of sum duration of all stops in a trajectory over total time of Trajectory (mean~43, median~41)

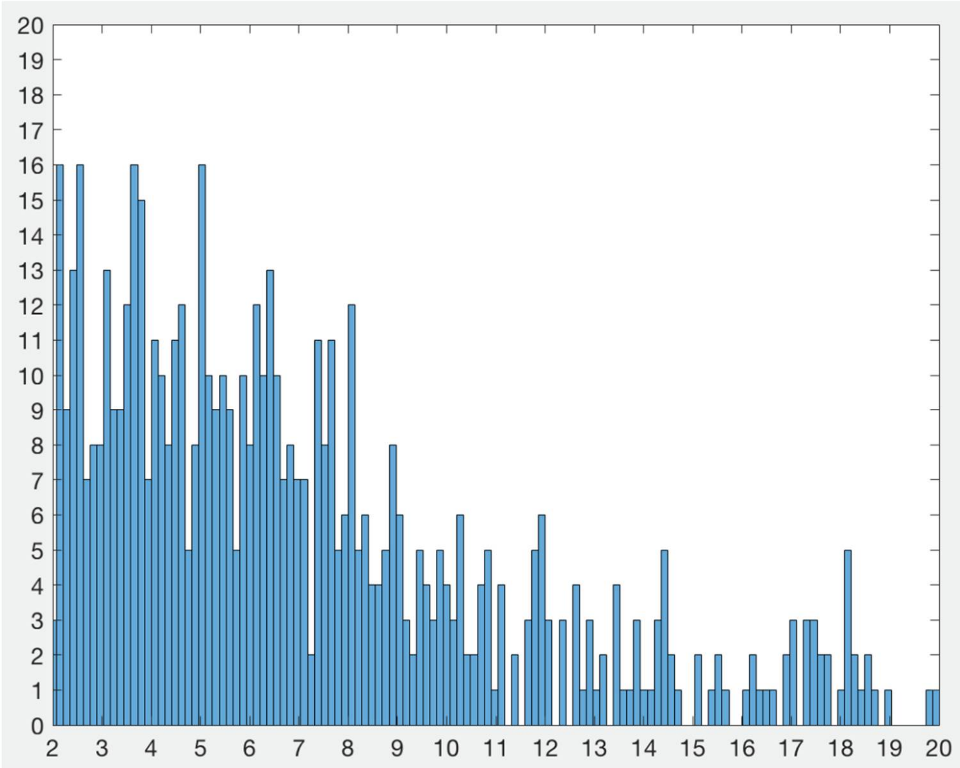

Figure 8. Percentage of mean Stop time per Trajectory (mean ~22s, median ~15s)

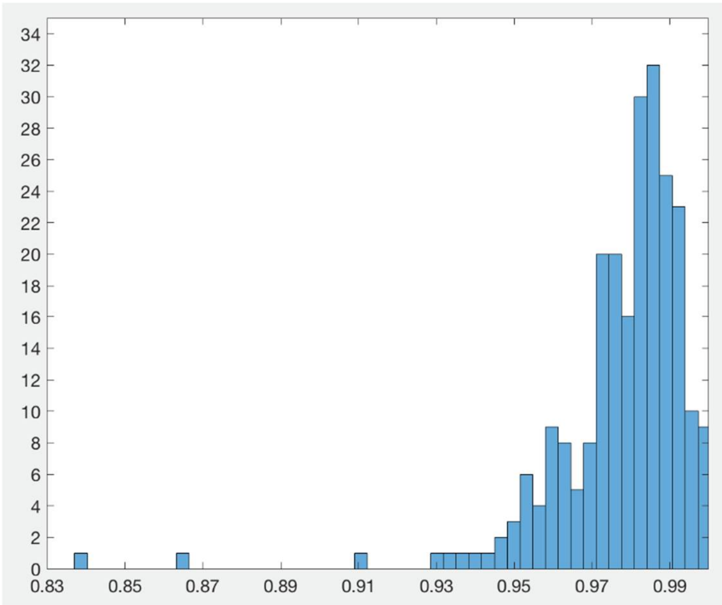

Figure 9. Ratio between zero symbols and the length of the sequence of A constraint

Following the initial quantitative analysis, that consisted of the trajectory duration analysis, the velocity statistics, the number of stops distribution, and the stop duration statistics, we now move to the qualitative trajectory calculus-based analysis.

We used ***QTC analysis*** in order to investigate ***interactions between people***. Firstly, we obtained trajectories from the dataset (which were pre-marked as being pairs, so as to have ground truth) and then we analyzed the pairs using QTC with three basic constrains and with a threshold of 10cm. The distribution of ***ratios between zero symbols*** in the A constraint (see table 1) and the ***lengths*** of the sequence is shown in the figure 9. As expected most values are close to 1 that means that most QTC symbols in A are zeros, which is what to be expected in the case of pairs moving together, either in parallel or in leader-follower relations (i.e. the distance usually remains constant). The distribution of the entropy for the same QTC symbols sequences is shown in the figure 10, and as expected it has very small values, given that the underlying distributions are heavily biased to one value (i.e. the probability of a "0" symbol is much higher than the probability of a "+" or a "-" symbol). In previous research [3], it has been shown how the ***composite-symbol distribution entropies*** of QTC-3D time-series (i.e. composite symbols made by the Cartesian product of various QTC-constraint symbols, not just the A constraint that was used here) can be used to distinguish leaders from followers for the more complex case of pigeons flying in three dimensions.

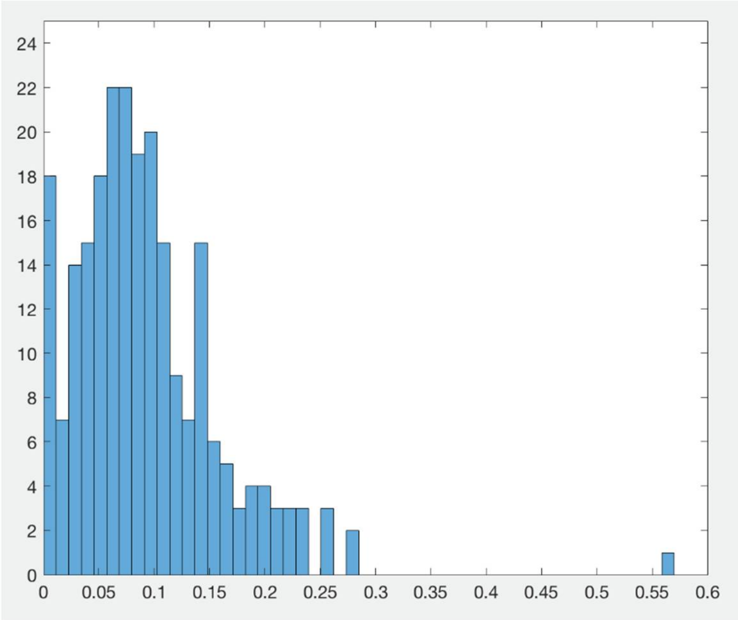

Figure 10. Entropy of the sequence of A constraint

Often when two people are moving as a pair, one of them takes the role of the leader while the other assumers the role of the follower. The other possible cases are ***parallel movement***, or you can have ***rotating leadership***. The ***fixed leader-follower*** case is usually apparent through the observation that when the leader slows down or accelerates the follower does the same too but with a small ***time delay***. So, we tried to apply QTC with variable time delay (gradually increasing an artificial time delay on one of the two trajectories and then creating the pair) on the pairs from the dataset.

Figures 11 and 12 illustrate our obtained results. In the figure 11 the orange line corresponds to the entropy of the original QTC symbol sequence (no time delay) while the blue line corresponds to the entropy of the QTC symbols vector generated with an artificial time delay in one of the two trajectories. Notice that in figure 11 the positive time delay corresponds to delay of the leader with respect to the follower; but in figure 12 the positive time delay corresponds to delay of the follower with respect to the leader. As expected a minimum arises only in Fig. 12: the minimum entropy is reached when we assume that the follower mirrors the leader with approximately 370msec delay.

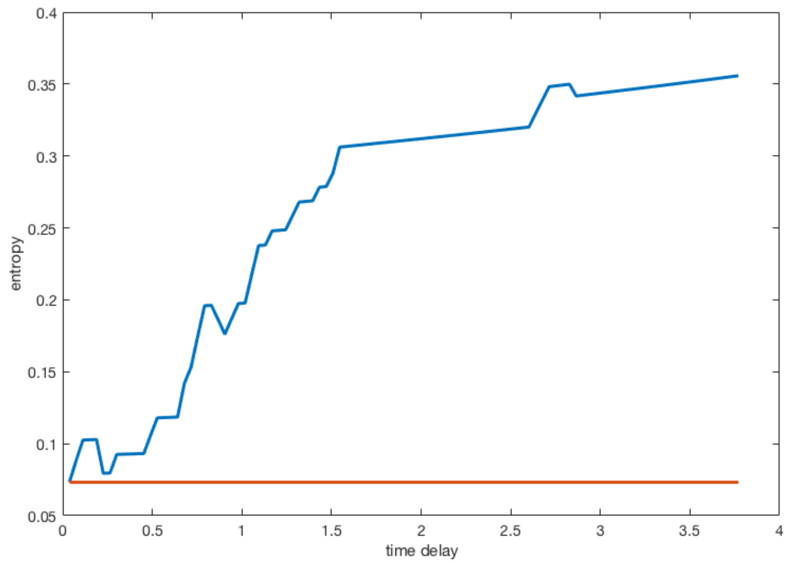

Figure 11. Entropy of the particular sequence of QTC symbols with and without time delay (orange and blue)

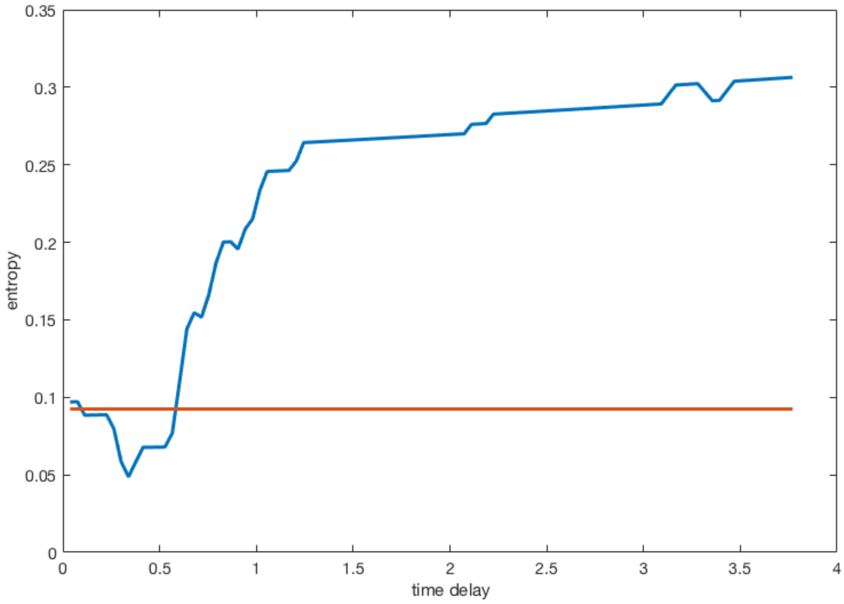

Figure 12. Entropy of the particular sequence of QTC symbols with and without time delay (orange and blue)

FUTURE STEPS

Further analysis and methodology standardization steps are taking place at the moment, together with development of methods for incorporation of the results into our social path planning algorithms. Some of the current and future steps include:

- Derivation of a compact representation of the results of the quantitative analysis. This representation consists of probabilistic automata: their vertices correspond to {entry/exit/stasis points} and their edges correspond to {walking segments}. On the vertices and the edges, we also supply associated temporal (duration) and spatial (velocity, curvature, location) distributions (in an analogous fashion to the models of [35]).
- Further discrimination between {leader-follower, rotating leadership, parallel walking, uncorellated movement} for pairs, and automated classification on the basis of the QTC symbol sequences of random pairs.
- Detection of "approach towards interaction" & "detach from interaction" episodes, and study and modelling of the QTC symbol sequences during the episodes, as well as associated quantitative parameters (for example, associated to personal space constraints).
- Incorporation of the above results towards tuning social path planning algorithms for robots, such as [11-12].
- Utilization of the above results towards optimization of building structures as well as locations of specific landmarks and functions within buildings, in order to achieve the desired people flow, people stop, and people interaction patterns within buildings.

CONCLUSION

Towards the fluid and natural co-habitation of spaces by humans and robots and their co-operation as our primary purpose, but also towards compact modeling of human motion and interaction patterns within public spaces as a secondary purpose, in this paper we have presented initial steps of a methodology, consisting of both quantitative as well as qualitative analysis. Qualitative Trajectory Calculus (QTC) was utilized, offering a powerful set of tools towards selectable-granularity abstraction of relative trajectories of moving entities, while preserving essential aspects of their interaction. Furthermore, probabilistic modeling of temporal and spatial aspects of the human trajectories, as well as their stasis episodes, was brought to use.

Initial results were presented for the case of a dataset consisting of human motions and interactions within a Japanese shopping mall, the ATC dataset. Trajectory duration statistics, statistics of walking and stasis episodes numbers and durations, velocity distributions were presented. Furthermore, qualitative analysis using minimal QTC and entropy analysis, uncovered leader-follower relations as well as the mean delay time in them. Importantly, future steps were presented, towards creating standard and compact representations of such results, towards further discriminating between many possible types of trajectory pairs, towards analyzing approach-detach results, and towards utilizing our results for human-robot interaction as well as architectural & spatial design purposes.

The methods described and which are being further developed, are becoming increasingly important given the rapid rise of service robots and the need for human-aware navigation, maximizing the safety and comfort of humans while preserving social norms such as proxemics and personal spaces, ultimately towards a future where robots will help improve human lives.

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