Pedestrian Stride Frequency and Length Estimation in Outdoor Urban Environments using Video Sensors

Nicolas Saunier, Ph.D., Assistant professor (Corresponding author)
Department of civil, geological and mining engineering
École Polytechnique de Montréal, C.P. 6079, succ. Centre-Ville
Montréal (Québec) Canada H3C 3A7
Phone: +1 (514) 340-4711 ext. 4962
Email: nicolas.saunier@polymtl.ca

Ali El Husseini, Undergraduate student
Department of civil, geological and mining engineering
École Polytechnique de Montréal, C.P. 6079, succ. Centre-Ville
Montréal (Québec) Canada H3C 3A7
Email: ali.el-husseini@polymtl.ca

Karim Ismail, M.A.Sc.
Lecturer, Department of Civil Engineering
Carleton University
1125- 3432 Colonel By Drive
Ottawa, ON, Canada K1S 5B6
Email: karim.ismail@alumni.ubc.ca

Catherine Morency, Ph.D., P.Eng., Assistant professor
Department of civil, geological and mining engineering
École Polytechnique de Montréal, C.P. 6079, succ. Centre-Ville
Montréal (Québec) Canada H3C 3A7
Email: cmorency@polymtl.ca

Jean-Michel Auberlet, Ph.D., Research scientist
Université Paris Est,
LEPSIS, IFSTTAR
58 boulevard Lefèbvre, F-75732 PARIS Cedex 15, France
Email: jean-michel.auberlet@inrets.fr

Tarek Sayed, PhD. P.Eng., Professor
Department of Civil Engineering
University of British Columbia
Vancouver, BC, Canada V6T 1Z4
Email: tsayed@civil.ubc.ca

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ABSTRACT

Amid concerns for the environment and public health, there has been recently a renewed emphasis on active modes of transportation, i.e. walking and cycling. However, these modes have traditionally received research and practice focus secondary to motorized modes. There is consequently a lack of pedestrian data, in particular microscopic data, to meet the analysis and modeling needs. For instance, accurate data on individual stride length is not available in the transportation literature. This paper proposes a simple method to extract automatically pedestrian stride frequency and length from video data collected non-intrusively in outdoor urban environments. Pedestrian walking speed oscillates during each stride, which can be identified through the frequency analysis of the speed signal. The method is validated on real world data collected in Rouen, France, and Vancouver, Canada: the root mean square errors on stride length are respectively 6.1 and 5.7 cm. A method is proposed to distinguish pedestrians from motorized vehicles and used to analyze the 50 min of the Rouen dataset to provide the distributions of stride frequency and length.

INTRODUCTION

Walking is a key non-motorized mode of travel and a vital component of most trips. Many road agencies have developed programs aimed to reduce traffic emissions by promoting less polluting forms of transportation such as walking and cycling. Public health researchers (agencies) also see in non-motorized modes of travel an opportunity to increase the level of physical activity among population at risk. Developing a better understanding of pedestrian movement is vital for improving the design methods of non-motorized and sustainable modes of travel. Such understanding can also increase the accuracy of behavioral models trying to link physical activity, health problems such as obesity, neighborhood design and travel behaviors. As well, pedestrians sustain the highest share of fatal road collisions among non-motorized modes of travel. Therefore, non-motorized modes of travel are receiving more emphasis in transportation engineering as the public and policy makers become more aware of issues of urban sustainability and energy supply, and health concerns regarding the lack of physical activity of the population.

However, these modes of travel, and walking in particular, have traditionally received research and practice focus secondary to motorized modes. The consequence is that there is a lack of pedestrian data, in particular microscopic data, to meet the analysis and modeling needs. For instance, accurate data on individual stride length are not available in the transportation literature. A previous project aiming to estimate the potential gain in physical activity for individual switching from a motorized mode to walking for short trips relied on simple estimations of stride length to convert distances into steps (1) (2). General hypothesis also had to be formulated regarding the average speed of walking and inherent energy expenditure. There is little research that discusses pedestrian stride length and the validity of currently used values.

Pedestrian data can be collected with various levels of automation. As manual data collection is expensive, time-consuming and error-prone, there are ongoing efforts to develop automated video-based methods. A video analysis system was developed to detect and track automatically all moving objects for road safety analysis (3) (4). It can also detect and track pedestrians and was successfully applied to the collection of walking speed data (5) and the study of pedestrian-vehicle interactions for safety analysis (6) (7).

This work presents a further use of pedestrian microscopic data, i.e. trajectories. Gait is the pattern of movement of the limbs of animals, including humans. This work deals with pedestrian walking gait, which is usually described by the following walking parameters: the walking velocity v, the stride frequency f and the stride length l, which are related by the following relationship $v = f \times l$. During the preparation of (5), the display of pedestrian walking speeds extracted from video data showed that speed fluctuates periodically at each stride (see FIGURE 1 and FIGURE 2f,k): identifying the strides becomes thus possible and permits to measure stride frequency and length. While there has been much research on pedestrian walking speed, stride length is not so commonly measured, even less automatically non-intrusively in the field. Distributions based on empirical measures are crucial for studies trying to estimate the impact of a shift from motorized modes to active transportation on the level of physical activity. Commonly, simple average estimations are used to translate distances into steps and energy expenditure (1) (2). This is a very crude model of the reality. Producing distributions of stride length and walking speeds, according to various conditions or population attributes would greatly enhance the current estimation methods. The current paper establishes the basis for such contributions. It presents an automated method for the estimation of stride frequency and length from trajectory data extracted from video data. The background of this work is presented in the next section. It is followed by a description of the proposed methodology, which is then validated on a new video dataset collected at an urban intersection in Rouen, France. Finally the paper is concluded and future work is discussed.

BACKGROUND

Active Modes of Transportation

Walking is a sustainable travel choice that brings benefits to the walker and to the environment. Actually, active transportation has many positive outcomes: it can help reduce greenhouse gas emissions, traffic congestion or physical inactivity and its related health problems. In fact, active transportation has been related to many positive health outcomes: lower body mass index, blood pressure, cholesterol level and triglyceride concentrations (8) (9). In a study carried out in the Atlanta region, each additional kilometer walked per day was associated with a 5% reduction in the likelihood of obesity (10). In Finland, active commuting to work was found to reduce the risk of ischemic stroke among adults (11).

Recommendations for physical activity set a level of 10,000 steps per day for an adult in order to be active, which equals about one hour of moderate walking, five days a week (12) and accounts for a distance of five miles (13). For children, the recommended level is 12,000 steps for girls and 15,000 steps for boys aged 6 to 12 (14). Increasing the energy expenditure through walking is a valuable way to bring health benefits to the population (12). However, few attempts have been made to experimentally measure the number of steps required to cover a specific distance and assist in the development of strategies to make travel choice one way of improving public health. In the current context of declining shares of active modes of transportation but increasing interest towards them, it is important to update the current models to allow for relevant and integrated simulations. Transportation plans, policies and projects will hence be evaluated using comprehensive tools that explicitly assess the role of active transportation in the overall mobility of individuals.

Pedestrian Walking Stride Frequency and Length

Although most of the data on walking parameters comes from biomechanics and transportation research, there has been recently a strong interest in this data from the field of structural engineering. The closure of the London Millennium Footbridge in 2000 focused the attention on footbridge dynamic behavior under human loading (15). A good overview of the research is given in (15): in particular the ranges for the walking parameters found in the literature are given in TABLE 1. A more comprehensive literature review of walking speeds studies is available in (5). It is generally assumed that the measured data for all parameters follows the Gaussian probability distribution function. Differences are also reported in (15): "walking parameters and, in particular, free speed are influenced by physiological and psychological factors, such as biometric characteristics of the walker (body weight, height, age, gender), cultural and racial differences, travel purpose, type of walking facility". The last source of variability is intra-subject variability, as walking parameters change in time for the same pedestrian.

Pedestrian stride frequency was measured around 2 Hz in a controlled experiment described in (16). In (1) and (2), simple average values were used for different age groups: for adults, 1 mi is supposed to account for 2000 strides, which was increased by 10 % for elderly people, and proportionally to the height for young people.

Automated Pedestrian Data Collection for Transportation

Data collection in biomechanics and structural engineering is typically done in controlled experiments where pedestrians are instrumented or walk on surfaces embedded with sensors (e.g. force sensors) (15). Video sensors are the most common way to collect pedestrian data, in particular in real settings. Video sensors have several advantages. The first is that video sensors are minimally intrusive and capture naturalistic pedestrian movement with limited risk of attracting the attention of observed subjects, who could behave unnaturally if they were aware of being watched (17). Other advantages include the relative ease of installation, the rich data that can be extracted (i.e. complete trajectories), the large area that can be covered and their low cost. Video data may be analyzed manually, semi-automatically or fully automatically. Methods that are not completely automated are time-consuming and therefore limited in terms of data volume, and have varying levels of accuracy. Computer vision techniques may be used to address these shortcomings.

The transportation literature contains few studies that involved applying computer vision techniques to collect pedestrian data in real settings, especially in busy "open" outdoor urban environment, such as areas around an intersection or transit hubs. Open refers to the mixed traffic, including motorized vehicles and pedestrians, the variable environment, the multiple flows of moving objects that may enter and leave the scene, and stop for varying amounts of time in the field of view. Collecting observational data for pedestrians is particularly challenging due to the less organized nature of pedestrian traffic compared to vehicular traffic (18). Automated pedestrian data collection in such environments remains a largely unsolved problem in the field of computer vision. Most published work is limited to idealized conditions and small datasets, e.g. with heads and feet present all the time (16), low pedestrian volume (19) (20), or in heavily controlled indoor experiments including markers on pedestrians (16) (21). The collected datasets are typically small and in some cases, require significant manual input to correct the automated results and to supplement with additional data (20). The readers are referred to (5) (22) (23) for more details on the alternative computer vision methods that may be employed to detect and track pedestrians.

The periodicity of measurements of walking pedestrians as a function of time was previously noticed in the literature (16) (24), and used to extract stride frequency and length (the force applied on the ground in (25)). However, no previous work used the walking speed for that purpose.

METHODOLOGY

Feature-based Tracking

A feature-based tracking system was initially developed for vehicle detection and tracking as part of a larger system for automated road safety analysis (4) (26). Feature-based tracking is preferred because it can handle partial occlusion and does not require any special initialization. Tracking features is done through the well known Kanade-Lucas-Tomasi feature tracker. Stationary features and features with unrealistic motion are filtered out, and new features are generated to track objects entering the field of view. Since a moving object can have multiple features, features must be grouped using cues like spatial proximity and common motion. The grouping method described in (27) was extended to handle intersections (26). Tracking performance was deemed sufficient for the original road safety analysis, as well as for pedestrian data collection and safety analysis: walking speeds were validated in (5) for day- and night-time conditions with an excellent agreement between manual and automated walking speed values (respective root mean square error of 0.0725 m/s and 0.0548 m/s).

Finally, an important step is to perform the analysis on a feature trajectory for each road user instead of the trajectory resulting of the average of its corresponding set of features, which suffers from strong discontinuities. Therefore, the feature that is tracked for the longest time is chosen to represent each road user (and considered to be its trajectory).

Computing the Stride Frequency and Length

The stride frequency f may be defined in two ways. The definition used in this paper is the vertical walking frequency, which is the number of times a foot touches the ground in a time unit, while the horizontal or lateral walking frequency is the number of times the same foot touches the ground. The lateral stride frequency is therefore half the vertical one.

The method relies on the hypothesis that walking speed is periodic and its frequency is the stride frequency. Detecting the periodicity and estimating the frequency from a noisy signal, as is walking speed obtained from video data, is done in signal processing through spectral density estimation. The goal is to estimate the spectral density, or power spectrum, from a sequence of time samples of the signal. This can be done through a fast Fourier transform (FFT). The power spectrum is obtained by smoothing the speed time series, by subtracting its mean value, and then by computing the absolute value of the result of the

FFT of the signal. By observing the largest maxima in the power spectrum, the stride frequency may be extracted. The steps are the following:

1. Frequencies are searched in an reasonable interval $[f_{min}, f_{max}]$ for pedestrians (the range of 1 to 3 Hz is used in (24))
2. Frequencies are considered if their corresponding power is superior to a ratio α of the maximum power.
3. More than one frequency may satisfy the first two conditions. A maximum number of N_f frequencies are considered.
4. The final stride frequency f is obtained as a function of the remaining frequencies: two methods are tried, namely the mean of the remaining frequencies or the frequency for which the power is maximum among the powers at the remaining frequencies.

The parameters are listed in TABLE 2. The method may not find any frequency satisfying the conditions: this depends only on the frequency interval $[f_{min}, f_{max}]$ and the ratio α. The impossibility to find a frequency can be attributed to a pedestrian with an atypical speed profile, to significant changes in time, or to another type of road user. Sample speed profiles and their corresponding power spectrums for pedestrians and motorized vehicles are displayed in FIGURE 1: it can be seen that the peak in the power spectrum is more or less easy to identify, but a frequency can be found for all these examples with the right parameter settings. It should also be obvious that simple heuristic approaches counting the number of peaks or times the signal crosses its mean value would not yield results on all these examples.

Finally, the stride length is computed based on the distance traveled by the pedestrian over some period of time during which the stride frequency is supposed to be constant. The period of time considered in this work is the time duration Δt during which the object feature is tracked. It could be necessary to go into more details if walking parameters change too much in time. The distance d traveled is measured along the path of the pedestrian and the stride length l is computed as $l = \frac{d}{\Delta t * f}$.

Classifying Pedestrians and Motorized Vehicles

Open outdoor urban environment contain a mixture of road users. Feature-based tracking provides the trajectories of all road users which must then be classified by road user type for further analysis. In this work, it is required to distinguish pedestrians from other road users (mostly motorized vehicles). A simple threshold on the maximum speed reached by road users during their existence was used for classification in (5) and (28). A more sophisticated method was developed in (7), relying on the learning of labeled motion patterns and classification by trajectory similarity. In the present work, an additional cue is proposed for classification: speed profiles are different for pedestrians and motorized vehicles, the former exhibiting periodicity that is exploited to measure stride frequency and length.

The classification is based on the following characteristics: the stride frequency f and length l, the frequencies f' found in the interval $[0, f_{min}]$, and the number of times per second that the speed profile goes through its mean value denoted $n_{oscillations}$. The method for classification is thus:

- If a frequency f can be computed, and $n_{oscillations} > n_{pedestrian\ oscillations}$
  - If $l < l_{pedestrian}$, the road user is classified as a pedestrian
  - Else the road user is classified as a motorized vehicle
- Else if a frequency f' can be computed and $n_{oscillations} < n_{pedestrian\ oscillations}$
  - The road user is classified as a motorized vehicle
- Else the road user has an unknown type

The threshold parameters $n_{pedestrian\ oscillations}$ and $l_{pedestrian}$ were found easily by trial and error. Speed profiles and the corresponding power spectrums are shown in FIGURE 1 for a sample of pedestrians and motorized vehicles: it can be seen that all pedestrians satisfy the first condition on frequency f and oscillations, while the motorized vehicles satisfy the second condition on f' and the oscillations. The method performance is evaluated in the next section.

EXPERIMENTAL RESULTS AND ANALYSIS

Description of the Dataset

Two datasets are used to validate the performance of the proposed method and to illustrate the pedestrian data that may be extracted from video data. The main dataset was collected in Rouen, France, in May 2010, during the morning. The duration of the video sequence is about 50 min, during which traffic is mixed with significant pedestrian presence and low vehicle speeds. The second dataset was collected in Vancouver, Canada, in July 2007, during the late afternoon before a large public gathering in the Downtown area to watch fireworks (5). The duration of the video sequence is approximately 2 minutes and features groups of pedestrians. Camera calibration is necessary to obtain accurate measurements of walking parameters in world coordinates. It was performed using various traffic scene features and the method described in (29). The code for the computation of walking parameters and their validation was written in Matlab, using the signal processing toolbox FFT function.

Validation

Data was collected manually in the two datasets to validate the method. Pedestrian trajectories were screened by replaying the video with an overlay of the pedestrian feature trajectory. The following pedestrian trajectories were excluded from the validation datasets: 1) trajectories that involve more than one pedestrian, mainly due to tracking errors, 2) trajectories of pedestrians whose feet are not visible in the recorded video for an extended period of time, 3) trajectories of non-pedestrian road users such as vehicles, strollers, cyclists, and animals, and 4) extra trajectories of pedestrians with more than one trajectories (only one trajectory should be included in the validation set to avoid double counting). Examples of excluded validation trajectories from the Vancouver dataset are shown in FIGURE 2a-d. The longest period of time during which the largest number of complete strides were made was identified. The stride frequency is then derived, and the stride length is computed based on the distance traveled by the pedestrian as measured by video analysis. 102 and 50 pedestrians were manually annotated respectively for the Rouen and Vancouver datasets. FIGURE 2e-k show a number of pedestrian trajectories and corresponding speed profiles in time.

Stride frequency and length can then be computed automatically for all pedestrians in the validation datasets and compared to the manual reference data. The accuracy is measured by the root mean square error (RMSE) over each validation dataset. The influence of the method parameters was systematically evaluated: the parameter settings are listed in TABLE 2. Depending on the parameters, no frequency in the power spectrum may satisfy the conditions: in such a case, the stride frequency and length cannot be measured by the proposed method.

FIGURE 3 shows the performance of the method on the two datasets, measured by the RMSE for the stride frequency, and the number of pedestrians with calculable stride frequency. The first remark is that there is a trade-off between accuracy and the number of pedestrians with calculable stride frequency. As can be predicted from the proposed method, this number decreases as the ratio α increases and the pedestrian frequency range $[f_{min}, f_{max}]$ becomes narrower (it is obviously independent of the selection method). Intuitively, the more selective the method is (by increasing α or narrowing $[f_{min}, f_{max}]$), the fewer the number of pedestrians with calculable stride frequency, but the more accurate the result. It is actually a little more complex, with differences for the two datasets: accuracy increases as the ratio α increases, except for large frequency ranges $[f_{min}, f_{max}]$ on the Vancouver dataset: this could be explained by the longer trajectories and changing stride frequency in time. Regarding the frequency selection method, mean or maximum (see results on the first two rows of FIGURE 3), the mean consistently produces better results. Overall, the performance increases as the maximum number N_f of frequencies considered for selection increases, for both methods of frequency selection (for lack of space, plots similar to the ones in FIGURE 3 are not included). The comprehensive performance evaluation over a portion of the parameter space allows picking good settings, by choosing a trade-off between performance and the number of pedestrians with calculable stride length. Setting a required minimum number of pedestrian with calculable stride frequency, “optimal” parameter settings were chosen (see TABLE 2) and the corresponding performance are listed in TABLE 3, with the best performance over all parameter settings: these results make clear that it is useful to trade a bit of accuracy to obtain more measurements of pedestrian stride frequency and length. The method performance is similar for the two datasets.

Results

All road users are tracked in the Rouen video sequence, their stride frequencies and lengths are computed, and they are classified using the proposed method. Using the values $n_{pedestrian\ oscillations} = 1.12$ and $l_{pedestrian} = 1.2\ m$ and the optimal settings for the computation of stride frequency and length (see TABLE 2), the classification performance is measured on the validation dataset, augmented with 94 motorized vehicles. The confusion matrix is reported in TABLE 4. Performance is deemed sufficient to apply the method to the whole dataset. It should be noted that other cues can be added to improve the results, based on maximum speed (5), trajectory location (7), and image appearance (30).

The distributions of stride frequency and lengths are displayed in FIGURE 4, and the statistics for all the datasets are provided in TABLE 5. These results are within or close to the range reported in other studies in the literature (TABLE 1). Interestingly, the stride frequency and length are both lower in the Vancouver dataset than in the Rouen dataset. Apart from population variations, this can be attributed in Vancouver to the slope of the street covered by the camera (while the ground is flat at the Rouen intersection), the time (evening) and the type of the street (residential), reinforced by the presence of pedestrians going to an outdoor event. One can also notice the difference in the mean stride frequency and length between the annotated portion and the whole of the Rouen dataset, as well as the extreme values, small and large, in the distribution presented in FIGURE 4: the most likely causes of these observations are that there may be a population of people walking more slowly in the whole dataset, as well as tracking and classification errors (although conditions on minimum displacement were enforced, the tracked object may be the bag of a person, or another type of road user).

The conditions to collect pedestrian walking parameters successfully is the quality of the video data: as was noted in previous studies (5) (28) (7), the size of pedestrians in images is the most important factor, typically requiring high resolution videos (superior to 1080 by 1440 pixels) to cover large enough areas for interesting studies. Another important factor is the frame rate. A first attempt at developing the method proposed in this paper was made on video data collected in Montreal using network cameras: the video was highly compressed, but more importantly, the frame rate was only 15 images/s, compared to 30 and 25 images/s respectively for the Vancouver and Rouen datasets. This has an obvious impact on the possibility to distinguish short speed time variations.

Another difficulty is caused by long trajectories in which pedestrians stop for a moment, then walk again, and change pace (see for example FIGURE 2f). The periodicity of the speed will change in time and it will be difficult for the proposed method to identify the stride frequency. A solution is to do the analysis at multiple scales in order to identify these variations. Being able to measure all the walking parameters in time will yield a better understanding of pedestrian behavior, how people adapt their gait depending on the environment, other pedestrians, motorized traffic, and street crossing.

CONCLUSION

This paper proposed a simple method to collect pedestrian walking parameters, namely stride frequency and length, from real world video data collected at urban intersections. The method is general and could be applied to any pedestrian speed profile obtained through other means, e.g. using intrusive or non-intrusive sensors as in this work. The analysis of the power spectrum and the speed profile provided also a simple but surprisingly effective cue to distinguish pedestrians from motorized vehicles, which can supplement other methods. The approach was validated on two datasets, collected in Europe and North America, and yielded satisfying results, e.g. the error on stride length is 5.7 and 6.1 cm.

It is not yet possible to update the work presented in (1) (2) as the models require a distribution of the stride length for various age groups, which cannot be determined automatically in video data collected in outdoor urban environments. Future work should address long pedestrian trajectories and study how pedestrian behavior adapts to the environment. Now that an automated method is available to extract walking parameter from video data, the variability of these parameters should be investigated across populations of pedestrians, as a function of body weight, height, age, gender, travel purpose, type of walking facility, and across time for the same pedestrians.

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TABLE 1 Ranges for the walking parameters from the literature review done in (8). Note that only two studies were found for the stride length

Walking parameter	*Range of the mean*	*Range of the standard deviation*
Walking speed (m/s)	1.19 – 1.60	0.15 – 0.63
Stride frequency (Hz)	1.82 – 2.0	0.11 – 0.186
Stride length (m)	0.75 – 0.768	0.07 – 0.098

TABLE 2 Different settings for the computation of pedestrian stride frequency and length

Parameters	***Settings***	***Optimal Settings***
Pedestrian frequency range $[f_{min}, f_{max}]$ (Hz)	[0.8, 3.2], [1.0, 3.0], [1.2, 2.8], [1.4, 2.6], [1.6, 2.4]	[1.4, 2.6]
Ratio α of the maximum power	0.10, 0.15, ..., 0.40	0.15
Maximum number N_f of frequencies considered for selection	5, 10, …, 30	10 (Rouen dataset) 20 (Vancouver dataset)
Frequency selection method	mean, max	mean

TABLE 3 Performance of the method and number of pedestrians with calculable stride frequency for the chosen optimal settings (see TABLE 2). Between parentheses are provided the minimal RMSE values over all parameters settings with the corresponding number of pedestrians.

Dataset	***RMSE for stride frequency (Hz)***	***RMSE for stride length (m)***	***Number of pedestrians with calculable stride frequency***
Rouen	0.170	0.061	101
	(0.123)	(0.040)	(75)
Vancouver	0.161	0.057	42
	(0.090)	(0.030)	(11)

TABLE 4 Confusion matrix for the classification of road users

	Type predicted by the classification method		
True type	Motorized vehicles	Pedestrians	Unknown
Motorized vehicles	87	2	5
Pedestrians	6	95	1

TABLE 5 Results for the different datasets, including the validation datasets, with the manual and automated measurements

Dataset		***Stride frequency (Hz)***	***Stride length (m)***	***Number of pedestrians with calculable stride frequency***
Rouen	annotated dataset (manual)	1.908 ± 0.214	0.748 ± 0.139	102
	annotated dataset (auto)	1.901 ± 0.173	0.759 ± 0.163	101
	whole dataset	1.897 ± 0.147	0.678 ± 0.217	1253
Vancouver	annotated dataset (manual)	1.703 ± 0.311	0.625 ± 0.119	50
	annotated dataset (auto)	1.753 ± 0.174	0.679 ± 0.132	42

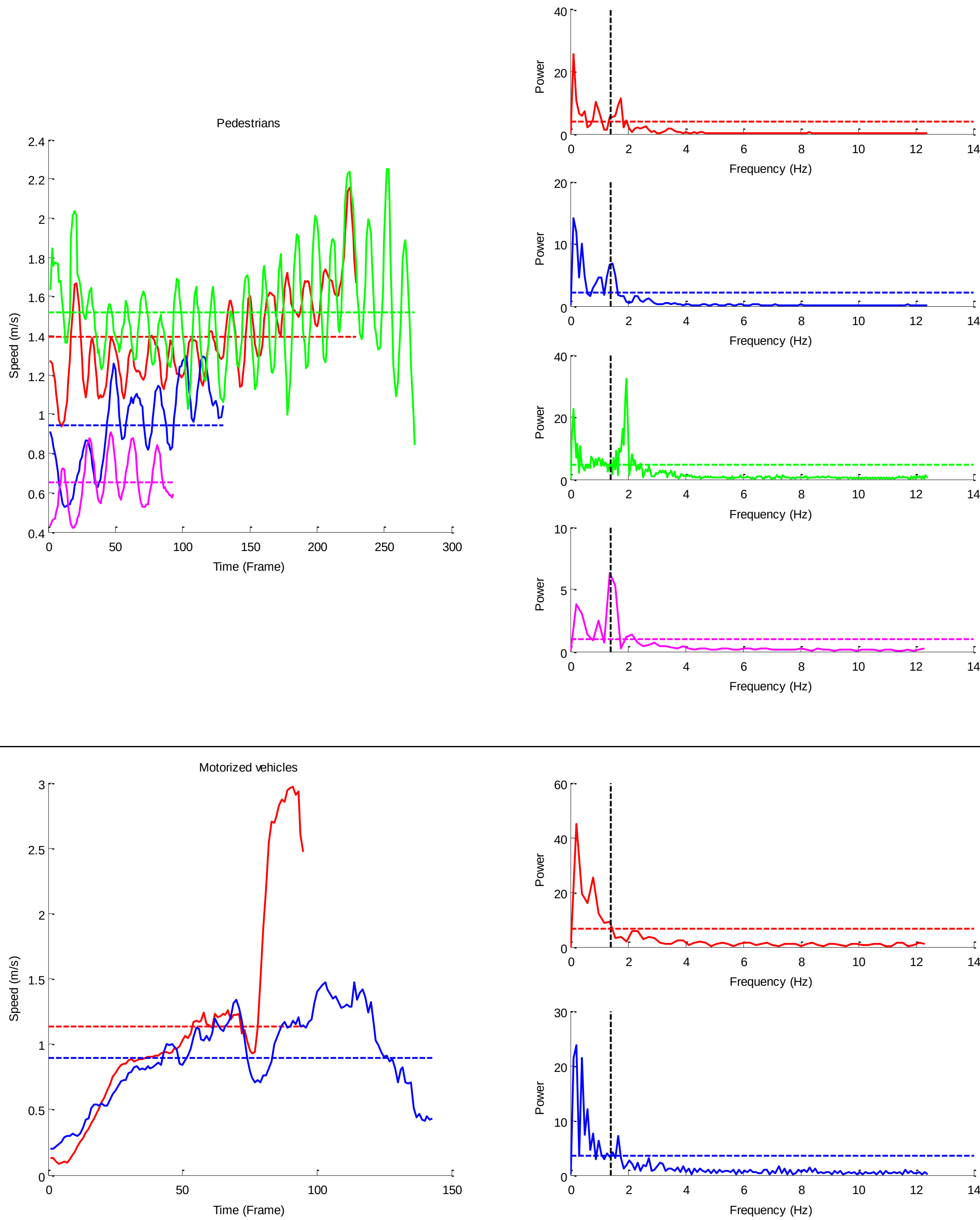

FIGURE 1 Speed profiles and the corresponding power spectrums for a sample of 4 pedestrians (top) and 2 motorized vehicles (bottom). The horizontal dashed line represents the mean of the speed for each speed profile, and the threshold α of the maximum power for each power spectrum. The vertical dashed black line represents the first frequency of the search range $[f_{min}, f_{max}]$ (the optimal settings in TABLE 2 is 1.4 Hz).

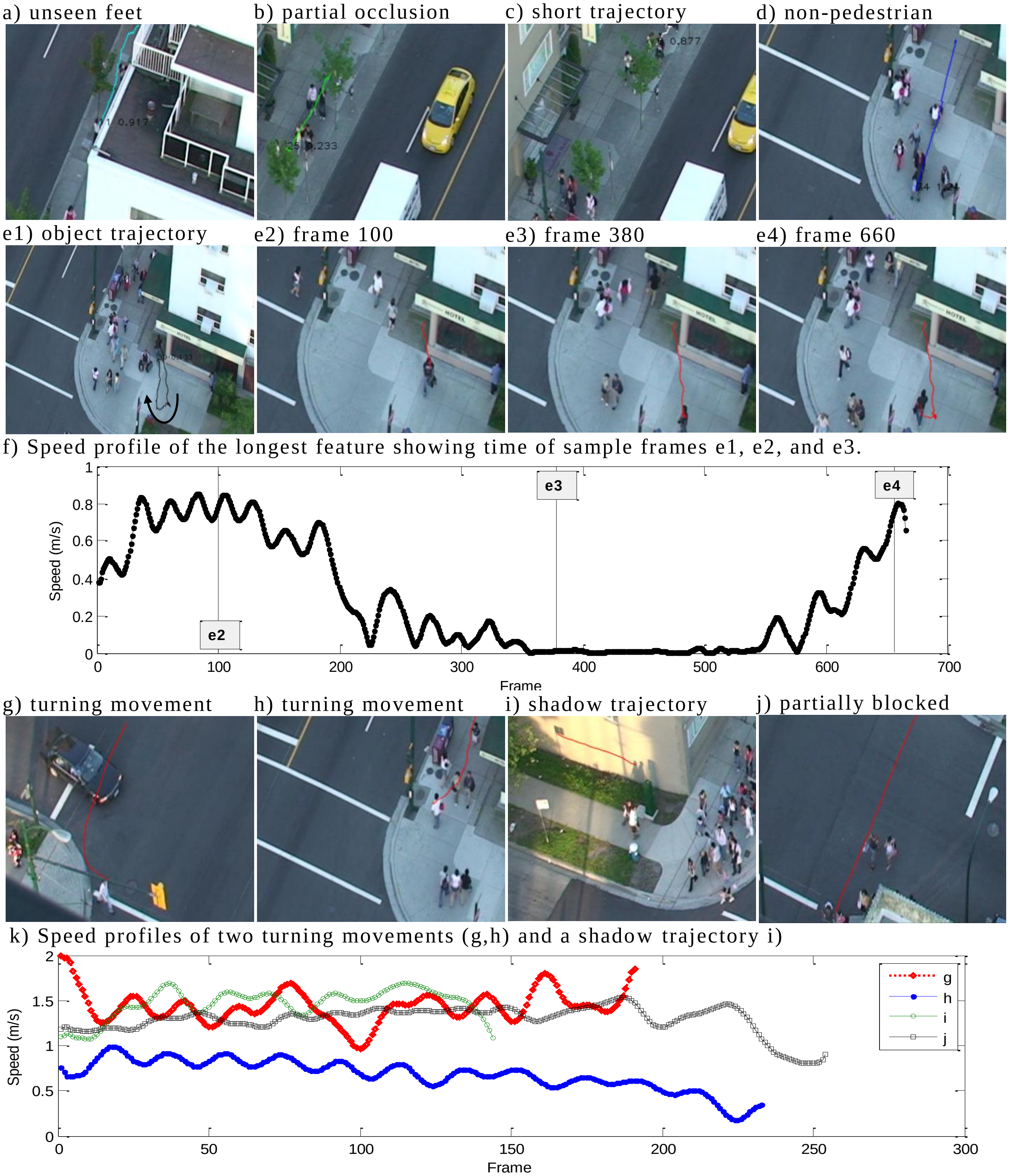

FIGURE 2 Sample trajectories from the Vancouver dataset. Figures a-d show trajectories excluded from validation due to visual obstruction of feet (a,b), trajectories of pedestrians making fewer than 5 strides (c), and non-pedestrians (d). Figures e1-e4 show sample frames of a pedestrian trajectory with an intermediate stop and Figure f shows the corresponding speed profile. Figures g,h,i, and j show non-typical trajectories included in the validation. Figure k shows their respective speed profiles.

Rouen dataset $N_f=10$ Vancouver dataset $N_f=20$

Mean frequency selection method

Maximum frequency selection method

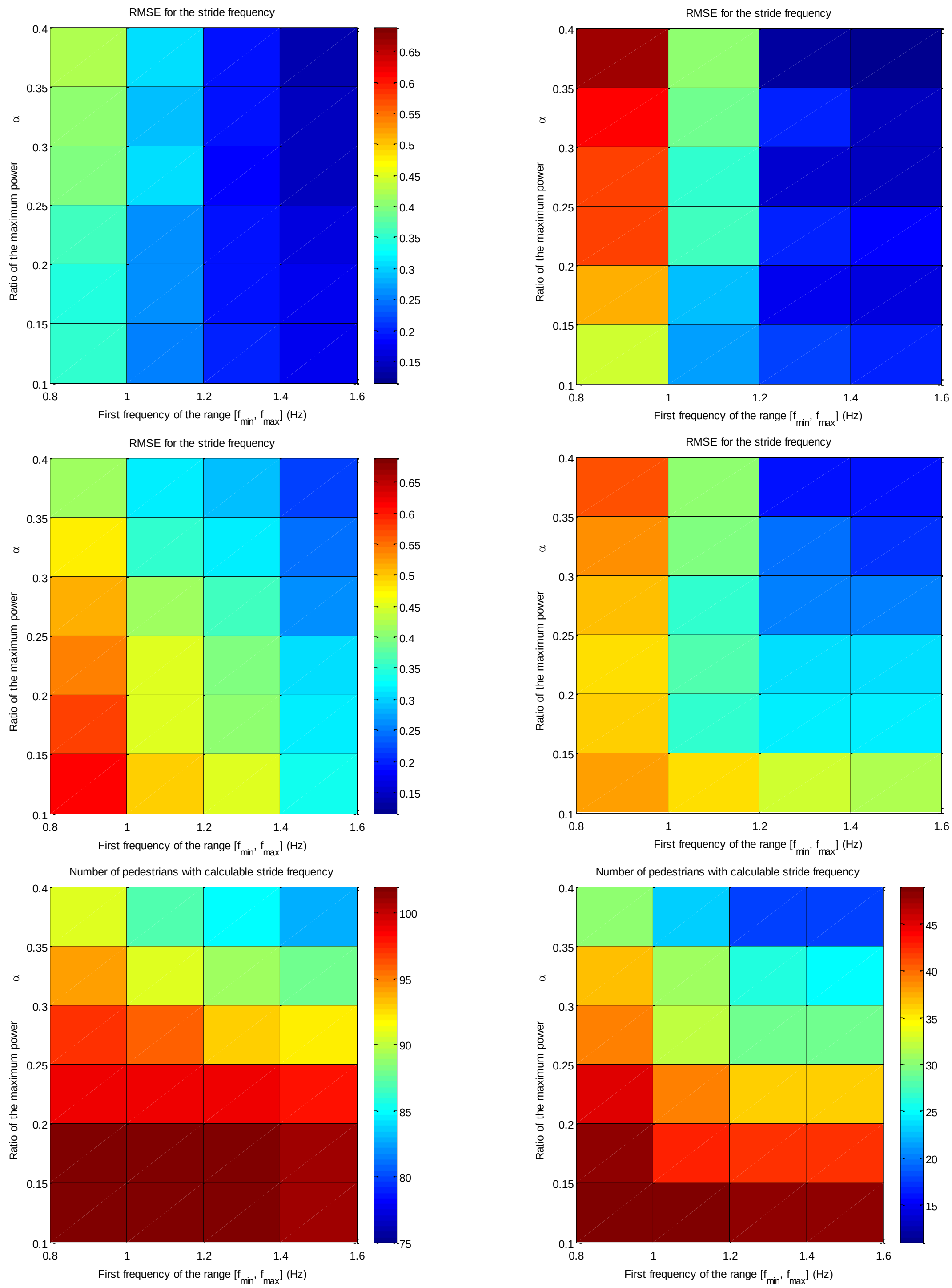

FIGURE 3 Performance of the method on the two datasets: the top two rows of figures show the RMSE for the stride frequency (on the same scale), respectively with the mean or maximum frequency selection method; the bottom figure plots the number of pedestrians with calculable stride frequency. The number on the x axis is the first frequency of the search range *[f_{min}, f_{max}]*, corresponding respectively to the frequency intervals [0.8, 3.2], [1.0, 3.0], [1.2, 2.8], [1.4, 2.6], [1.6, 2.4].

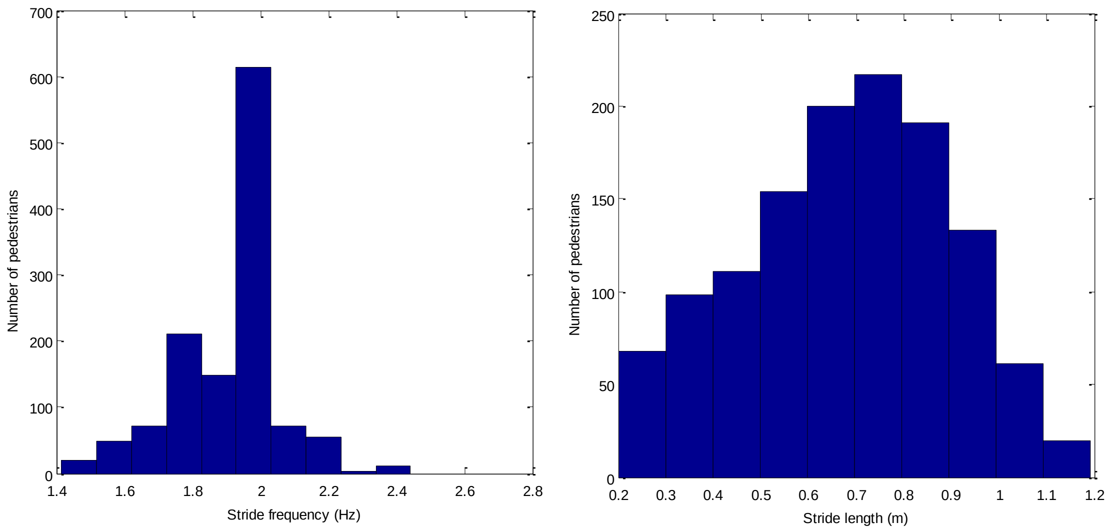

FIGURE 4 Distributions of the stride frequency and length for the Rouen dataset (50 min).