A Real-time Algorithm for Regional Crowd Counting Based on Survival Analysis Theory

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Abstract. This paper proposes a real-time algorithm for regional crowd counting based on survival analysis theory. Our algorithm can accurately calculate regional people flow in real time over a long period, which considers tourists’ stopping time as a type of survival time, and discretizes its continuous distribution probability as a proportion of stopping people in a monitoring region. Compared to other crowd counting methods, our algorithm calculates regional population in real time using a mathematical statistical model, which greatly reduces the dependence on hardware devices. Experiments in two real scenarios verify that the average accuracy of our algorithm is over 91% in comparison with 60% of sensing devices.

1. Introduction
Regional crowd counting is an important technical method of managing urban people flow and safety. Population counting techniques are currently applied in entrances and scenic spots in a variety of public places, such as supermarkets, subway stations, public bus stations, and scenic areas. Real-time monitoring of people flow in these scenarios provides real-time and quantitative information for public safety, market decisions, and resource allocation. Many population counting products and methods are now available to monitor people flow in real time, control people flow based on actual monitoring results, and maintain regional security.

Four major regional population counting techniques are: (1) base station signalling analysis [1]; (2) infrared and thermal imaging video monitoring statistics; (3) gate statistics; and (4) WiFi sniffing [2]. Although these techniques have been applied in various scenarios, each of them has some deficiencies, such as poor timeliness, blind spots existence and no gates at exits. In addition, a business model based on statistical models can reduce the dependence on hardware devices used with the above techniques. Some scholars [3-5] have analyzed factors in tourists’ stopping time using survival analysis models [6]. However, these studies were restricted to an analysis of factors on stopping time, and did not explicitly address the regional crowd counting issue.

Keeping the above research gap in mind, we propose a real-time calculation algorithm based on survival analysis theory. Our algorithm first fits the probability distribution of stopping time in a region, and then calculates the probability according to the fitted function. Lastly, the algorithm discretizes the continuous distribution into the proportion of people staying until a given time since entering. Based on that, we build a mathematical model to calculate population to achieve high accuracy in regional crowd counting.
The remainder of this paper is organized as follows. The second section mainly discusses domestic and international work relevant to regional crowd counting. The third section specifically addresses the regional crowd counting algorithm based on survival analysis theory. The fourth section discusses the two experiments in real scenarios. The last section provides a summary and discusses prospects for future work.

2. Relevant Work
In this section, we introduce existing regional crowd counting techniques used in industry and academia.

Regional crowd counting usually applied in industry include: (1) base station signaling analysis; (2) statistical method of scenic gates; and (3) WiFi sniffing. Base station signaling analysis [1] can analyze people sources and macroscopically calculate the number of people in a signal coverage area. However, it is not applicable in areas without signals. Also, since each calculation lasts half an hour, it has poor timeliness. The scenic gate statistical method refers to setting up gates in scenic entrances and exits, and automatically counting when tourists pass by the gates. Although this method is accurate, it is hardly applicable in China since many scenic spots have no gates at exits. Only the number at entrances can be counted. The WiFi sniffing method [2] calculates the number of people through terminals connected to WiFi. Although this method is simple, it cannot assume that all people are connected to WiFi. And some tourists may have more than one terminal. Therefore, it has low accuracy.

The hot research topic in academia is the method based on video analysis technology. It determines the number of people and the changes through the installation of cameras and the analysis of frames. This method can be divided into two groups, based on: (1) pedestrian (or crowd) detection; and (2) regression. The pedestrian (or crowd) detection method discovers people (or crowds) in images using a series of partial characteristics in images, and thus estimates the total number of people. This method can be further divided into two types, based on the kinds of objects detected: (1) methods based on pedestrian detection [7-10]; and (2) methods based on crowd detection [11-13]. The method based on regression [14-16] calculates the total number of people through learning the mapping relationship between image characteristics and people flow. The key of this method is the selection of image characteristics and regression models. Because this method does not require the direct detection of pedestrians or crowds in images or a trace of characteristic tracks, it is applicable to more scenarios than methods based on detection.

The above two groups of people flow counting methods are all dependent on hardware devices (gates, WiFi and cameras, etc.) to some extent. Several current studies are developing business models using statistical methods to avoid these restrictions. The domestic and international research hot topic is an exploration of factors [3–5] in tourists’ stopping times using survival analysis models [6]. But this research focuses on factors affecting stopping time, and it does not directly address the issue of regional crowd counting.

3. Regional Crowd Counting Algorithm Based on Probability Distribution of Stopping Time
In this section, we introduce the survival analysis theory model, provide our thoughts on the process of the algorithm and the estimation of probability distribution of stopping time, and discuss the hypothesis-testing methods used for the selection of probability distribution.

3.1. Survival Analysis Theory
Survival analysis [6] is a statistical method used to study the expected waiting time for the occurrence of an event, such as the survival time of a cancer patient, the residence time of a floating population in a city, or the duration of a marriage. Definitions of common concepts and terms in survival analysis theory are as follows.

Definition 1: Event refers to the end of a survival study that has been defined prior to starting a research. An event might be a patient’s death, departure of the floating population from a city, or divorce, depending on the research subject.
Definition 2: Survival time refers to the time an observed object experiences an event, from start to end. Survival is a broad concept. It not only refers to physical survival (in a medical sense), but also to the residence time of a floating population or the duration of a marriage.

Definition 3: Cumulative distribution function, expressed by \( F(t) \), is the probability that the survival time \( T \) of an observed object is less than or equal to \( t \). Its probability density function is expressed by equation (1):

\[
F(t) = P(T \leq t) = \int_{-\infty}^{t} f(s)ds = \int_{0}^{t} f(s)ds + \int_{t}^{\infty} f(s)ds = 0 + \int_{0}^{t} f(s)ds = \int_{0}^{t} f(s)ds
\]

\[
f(t) = \frac{dF(t)}{dt}
\]

Definition 4: Survival function, also called the cumulative survival rate, or just the survival rate, is represented by \( S(t) \). It refers to the probability that the survival time \( T \) of an observed object is greater than \( t \). It is the complement of the cumulative distribution function. It can be represented by equation (3):

\[
S(t) = P(T > t) = 1 - F(t)
\]

Based on the definition of the survival function, we have the following theorems:

Theorem 1: Normally, if \( t = 0 \), then \( S(t) = 1 \); if \( t \rightarrow \infty \), then \( S(t) \rightarrow 0 \).

Proof: can be directly derived from the definition of the survival function.

Theorem 2: The survival function is non-increasing. That is, if \( u \geq t \), then \( S(u) \leq S(t) \).

Proof: Because \( S(u) = 1 - F(u) \), \( S(t) = 1 - F(t) \), while the cumulative distribution function \( F(t) \) is a monotone increasing function, when \( u \geq t \) and \( F(u) \geq F(t) \), then \( S(u) = 1 - F(u) \leq 1 - F(t) = S(t) \).

In this paper, regional crowd counting can be modelled using survival analysis theory. The time when people enter a region is recorded as the starting time and the time when they leave as the end time. The stopping time equals the end time minus the starting time, which is the time that people visit and play in a region, i.e., the survival time of an event.

3.2. Overall Thoughts on Algorithm

Based on survival analysis theory, this section presents the specific use of the regional crowd counting method based on the probability distribution of stopping time.

We first divide the target region into several stopping spots based on the geographical environment. A stopping spot could be a checkpoint, scenic spot, or service facility such as a restaurant where tourists might stay. If the current time in a spot is \( t \), the number of stopping people is \( S_t \), the number of people entering in all \( t - i \) time points prior to \( t \) is \( IN_{t-i} \), and the proportion of tourists entering at time \( t - i \) and still staying at time \( t \) is \( \beta_i \), then the number of stopping people at the current time \( t \) can be derived as shown in equation (4):

\[
S(t) = \sum_{i=0}^{T} \beta_i IN_{t-i}
\]

Here, \( i \) is the stopping time scale, which could be one minute, two minutes, and so on. \( T \) is the maximum time that tourists stay in a spot at the current time \( t \), which generally can be set as \( k \cdot \mu \). The variable \( \mu \) is an average stopping time; \( k \) is a preset parameter, which can generally be set to 1.5. The variable \( IN_{t-i} \) is the number of people entering at time \( t - i \), which can be acquired by infrared or binocular equipment. The value of \( IN_{t-i} \) equals the number of people entering at time \( t - i \), acquired by equipment, minus the number of people entering at time \( t - i - b \), where \( b \) is a pre-set parameter, which can be set to 1.

In equation (4), the proportion of tourists entering at time \( t - i \) and still staying at time \( t \) is \( \beta_i \), which can be estimated from the probability distribution of tourists’ stopping time in a spot. If the stopping time is set as a random variable \( X \), then the probability distribution function is \( F(X) = P(X \leq x) \), which represents the probability that the random variable \( X \) is less than or equal to any real number \( x \), and the value of \( \beta_i \) can derived by equation (5):

\[
\beta_i = P(X > i) = 1 - F(i) = 1 - P(X \leq i)
\]
According to the definition of the probability distribution function $F(X)$, the value of $P(X > i) = 1 - F(i)$ in equation (5) represents the probability that the random variable $X$ is greater than the numerical value of $i$. But since the value of $X$, which is the stopping time of tourists entering a spot at time $t - i$ and still staying at time $t$, must be greater than the numerical value of $i$, $\beta_i$, the proportion of such tourists can be estimated from the probability $P(X > i)$.

At this point, the total number of people staying in spot $S_i$ at the current time $t$ can be calculated by equation (1). The total number of people staying in the whole region at the current time $t$ is the sum of $S_i$ in all spots.

The overall process of the algorithm is shown in Table 1.

Table 1. Algorithm for the number of people in a target region at time $t$

| Input | a series of numbers of people entering a target region prior to time $t$, $IN_{t-i}$ ($i$ is a stopping time scale), and a sample of historical stopping times $Q = (q_1, q_2, ..., q_j, ..., q_n)$, $q_j$ ($1 \leq j \leq n$) is the stopping time of the $j$th person, and $n$ is the sample scale. |
|---|---|
| Output | the number of people in a target region at time $t$ ($S_t$) |
| 1. | An estimate of $P(X \leq x)$, the probability distribution function of stopping time using a sample $Q$ of historical stopping times of tourists. |
| 2. | A selection of the best probability distributions from various probability distributions by a statistical test method |
| 3. | Calculation of $F(i)$ based on the probability distribution function $F(x)$, and calculation of the proportion of tourists $\beta_i$ entering and staying in a spot in a period from $t - i$ to $i$. |
| 4. | Calculation of the number of people flowing in a target region at the current time $t$, $S_t$, based on equation (4). |

In the following sections, we discuss steps 1 and 2 of the algorithm in detail. These concern the estimation of the probability distribution function of stopping time $X$ and the selection of the best probability distribution using a statistical method.

3.3. Estimation of Probability Distribution of Stopping Time Based on Survival Analysis Theory

An essential part of survival analysis theory is the estimation of survival functions based on available data. Three common types of modelling methods are parametric, nonparametric, and semi-parametric.

In our proposed algorithm, a random variable of survival time refers to the stopping time of people in a region at the current time. Based on survival analysis theory, if we assume that the survival time is compatible with a certain probability distribution, we can use the parametric method to estimate probability distribution parameters based on a sample of historical stopping times $Q$. Common survival-time probability distributions include logarithmic normal, gamma, Weibull, and exponential distributions. We chose the logarithmic normal distribution (introduced in Section 4.2) for the experiment in this study.

The lognormal distribution is the probability distribution of a random variable whose logarithm is normally distributed. If $X$ is a random variable that follows a normal distribution, $\exp(X)$ follows a lognormal distribution. Likewise, if $Y$ follows a lognormal distribution, $\ln(Y)$ follows a normal distribution. The density function, mathematical expectation, and variance of the logarithmic normal distribution are as follows:

$$f(x) = \begin{cases} \frac{1}{x\sqrt{2\pi}} \exp \left[ \frac{(\ln x - \mu)^2}{2\sigma^2} \right], & x > 0 \\ 0, & x \leq 0 \end{cases}$$

$$E(X) = \exp(\mu + \sigma^2/2)$$

$$Var(X) = [\exp(\sigma^2) - 1]\exp(2\mu + \sigma^2)$$

3.4. Statistical Test

To select the best probability distribution for stopping time, we statistically tested its estimated probability distribution. The Kolmogorov-Smirnov (K-S) test used in this study is one of several methods that test whether a random variable $X$ follows a pre-assumed probability distribution. Other methods include chi-square and Anderson-Darling tests. If a random variable $X$ represents stopping time, we use K-S test to determine whether it follows a probability distribution $F$ as follows.
**H₀:** the sample is from a population that follows the probability distribution \( F \); **H₁:** the sample is from a population that does not follow the probability distribution \( F \).

Here, \( F \) can be any survival-time distribution, such as lognormal distribution, Gamma, Weibull, or exponential distribution.

If \( F(X) \) is a pre-assumed distribution function and \( F_n(X) \) is an empirical distribution of \( X \), the test statistic \( D \) can be calculated as follows:

\[
D = \max |F(X) - F_n(X)|
\]

When the value of the test statistic \( D \) is greater than \( D(n, \alpha) \), \( D(n, \alpha) \) is the rejection threshold with \( \alpha \) significance level, **H₀** is rejected. That means that a random variable \( X \) does not follow a pre-defined theoretical distribution \( F \). In the contrary case, **H₀** is accepted.

### 4. Experiments

In this section, we describe how we applied the proposed regional crowd counting algorithm in two real scenarios, compared the results with the actual numbers from manual counting, and therefore determined an algorithm’s accuracy.

#### 4.1. Descriptions of Application Scenario and Evaluation Indicators

We applied the algorithm in the following real scenarios.

**Scenario 1:** a state-owned enterprise canteen in Hangzhou City. The experiment period was lunch (11:20 a.m. –12:10 p.m.) and dinner (5:00 p.m. –6:00 p.m.). The scene during the lunch time featured a large flow of people (greater than 14 persons per minute). The scene during the dinner time was characterized by a small flow of people (less than or equal to 14 persons per minute).

**Scenario 2:** a 5-grade scenic site (A) in Hangzhou City, one of the ten sites of the West Lake, which attracts numerous tourists every day. The number of tourists in the low season, high season, and golden week are listed in Table 2.

| Types of tourism seasons | Numbers of Tourists (single day) |
|--------------------------|----------------------------------|
| Low season               | 5-10 thousand                    |
| High season              | 10-20 thousand                   |
| Golden Week              | 20-40 thousand                   |

As shown in Table 2, scene A had a large daily flow of people. The number of tourists was several times greater during the golden week. The algorithm experimental results on such a scene would have great reference value.

In each scenario, we compared the results from the algorithm \( c_t \) at a certain time with the actual numbers \( r_t \) from manual counting. The accuracy \( A_t \) was our evaluation index. The specific equation is:

\[
A(t) = \left(1 - \frac{|c_t - r_t|}{r_t}\right) \times 100\%
\]

The average accuracy of the algorithm was the average of the accuracies at each time \( t \).

#### 4.2. Experiment Procedure and Results

4.2.1 Calculation of the number of dining people in the canteen. To calculate the number of people dining in the canteen in Scenario 1, we set up checkpoints at both the entrance and exit of the canteen, which collected the number of people at each time and the stopping time data of each individual. We used the proposed algorithm to calculate the regional population at a certain time using these data. We derived the algorithm’s accuracy by comparing it with the manual counting data. Sensing equipment is set up to count crowd at times of large people flow during the lunch time, and accuracy is calculated by equation (9). The result is shown in Figure 1.
Figure 1. A comparative chart between the number of people from the algorithm and the actual number during dining time in the canteen. (a) Dinner time (low people-flow), Algorithm accuracy = 93.32%; (b) Lunch time (high people-flow), Algorithm accuracy = 91.37%, accuracy of sensing equipment = 63.72%

As shown in Figure 1, the algorithm’s accuracy in small people-flow scenes is greater than in large people-flow scenes. But the accuracy is over 90% in either case, so the results are relatively accurate. In large people-flow scenes, the algorithm’s accuracy, 91.37%, is much higher than that of the sensing equipment counting (total entering number minus total leaving number), which is 63.72%, demonstrating the superiority of the proposed algorithm.

4.2.2. Calculation of scenic site population. In the case of the 5-grade scene A in Scenario 2, we compared the proposed algorithm with traditional counting with sensing equipment. The traditional
method required the installation of infrared pyroelectric sensing equipment at all entrances and exits, as well as in important monitoring spots in all scenes. The calculation was based on the real-time monitoring of the equipment. The source data of regional people entering and leaving was acquired by the sensing equipment. The real-time regional population was derived by subtracting the total number of leaving people from the total number of entering people. The result is as shown in Figure 2.

![Figure 2. A comparative chart between the number of people acquired by sensing equipment and the actual number](image)

Figure 2. A comparative chart between the number of people acquired by sensing equipment and the actual number

In Figure 2, the curve marked ‘REALLY’ represents the true value in the region acquired by video screens and derived by an artificial counting method, while the curve marked ‘ORIGINAL’ represents the regional population calculated from source data acquired by the equipment. As shown in Figure 2, the number of people acquired by the equipment was definitely invalid. After 11:00 a.m., the equipment could not provide real-time regional crowd counting. This is because monitoring equipment at various checkpoints had different accuracies. Under the influence of long-term accumulated errors, when the people flow continuously increased, accuracies continuously declined to a status of continuously missing counting after a certain point. When the calculated regional population from source data was negative, the truncation was zero.

We also calculated the real-time regional population by equation (4) using the proposed algorithm, which used the lognormal distribution modelling the probability distribution of stopping time. The result is shown in Figure 3, where the curve marked ‘REALLY’ represents the true value in the region (acquired by video screen shots and manual counting) and the curve marked ‘ALGORITHM’ represents the output value calculated by our algorithm. As shown in Figure 3, the accuracies of regional population were between 90% and 95% (data based on local areas, acquired by eight video screenshots, followed by manual counting). The number of tourists reached the maximum in a period between 3:50 p.m. and 4:20 p.m., and the deviation of the algorithm reached its maximum, which was between 8% and 10%.

![Figure 3. A comparative chart between the number of people from the algorithm and the actual number](image)

Figure 3. A comparative chart between the number of people from the algorithm and the actual number
Compared to the results from sensing equipment, our proposed algorithm based on the probability distribution are undistorted, stable, and reliable, so they can be applied in real-time monitoring and calculation of large people flows.

5. Conclusion and Prospects
In this paper, we propose a real-time algorithm for regional crowd counting based on the probability distribution of stopping time, derived from survival analysis theory, which greatly reduces the dependence on hardware devices. Our algorithm has been effectively verified, and the operational results match the actual situations. Therefore, the algorithm can achieve real-time monitoring of the number of tourists at stopping spots in scenic sites, and it provides support for decision-making regarding tourist flow management.

Prospects for future work include two aspects. The maximum stopping time parameter $T$ was empirically determined in our algorithm, which requires further theoretical exploration. Moreover, the estimation of the probability distribution of stopping time using parameters required a predefined empirical probability distribution, which restricts the application of the algorithm. Future research can focus on other methods, such as estimation based on nonparametric methods.

6. References
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