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Forum

Spatial technologies to strengthen traditional testing for SARS-CoV-2

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Advanced spatial and digital technologies may help us to take fuller advantage of limited testing resources to monitor the infection status of a large population in a cost-effective manner. Moreover, they may provide additional evidence to supplement results of nucleic acid testing (NAT) for severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) to decrease false-negative and false-positive rates.

SARS-CoV-2 causes coronavirus disease 2019 (COVID-19) that rapidly spread to more than 200 countries worldwide and was defined as a pandemic in March 2020. Reverse transcriptase (RT)-PCR, the most widely used NAT method for SARS-CoV-2, has routinely been used to confirm the diagnosis of COVID-19 since the beginning of this pandemic. However, according to existing research, the sensitivity of RT-PCR could vary substantially and be as low as 33% [1,2]. Although other traditional test methods, including computed tomography (CT) scanning and antibody tests, could be combined with NAT to improve the rate of diagnosis of COVID-19, all of these methods may suffer from limited testing capacity and materials (e.g., assays) during public health emergencies, especially at the early stages of the pandemic outbreak [3,4]. Advanced spatial and digital technologies may help us to take fuller advantage of limited testing resources to monitor the infection status of a large population in a cost-effective manner. Moreover, they may provide additional evidence to supplement traditional test results in order to decrease false-negative and false-positive rates (Figure 1).

Detecting clusters of cases of disease

Spatial epidemiological approaches in a Geographic Information Systems (GIS) environment, such as spatial clustering analysis, have previously been used to examine geographic distribution patterns of cases of disease; this has enabled efficient and cost-effective use of healthcare resources [5]. For example, local clustering analysis, one type of spatial clustering analysis, may detect and target limited resources at significant spatial clusters of COVID-19 cases in the region of interest; this would substantially reduce the cost of NAT and overcome the insufficiency of testing resources at an early stage of the pandemic. Moreover, space–time clustering analysis (e.g., Kulldorff's scan statistical method) may further reveal spatiotemporal clusters of cases. The results of these analyses could target limited testing resources to the regions of greatest need. However, the rapid spread of COVID-19 and the demand for identifying asymptomatic COVID-19 patients have challenged the paradigm of spatial epidemiology [6].

Providing additional evidence to supplement NAT results

Spatial lifecourse epidemiology (i.e., modern spatial epidemiology in the era of big data) utilizes advanced spatial, location-based, and artificial intelligence technologies to investigate long-term effects of dynamic environmental, behavioral, psychosocial, and biological exposures on human health, as well as the underlying mechanisms [7]. It has been recognized as a promising transdisciplinary paradigm to tackle the dynamic and multidimensional nature of emerging epidemics [8,9]. Real-time location data from mobile service providers and/or smartphone-based apps, the two important data sources of human movement in spatial lifecourse epidemiology, have played a critical role in curbing the COVID-19 pandemic. For example, combining individual movement patterns of COVID-19-infected patients and other citizens could determine an individual's contact history and hence the level of risk for COVID-19 infection; this method may be made more precise with the assistance of Bluetooth, which could better identify valid contact between individuals (e.g., when the distance between two persons is less than 1.5 m) [10]. The data of contact history have been incorporated into smartphone-based apps, and used at checkpoints in some countries, to determine whether an individual has traveled to a high-risk city within the previous 2 weeks.

Spatial and digital technologies could play a larger role in the detection of COVID-19 infection if data-sharing mechanisms and infrastructures (e.g., data-sharing protocols, intersystem interface, confidentiality protection mechanisms) have been properly stipulated and created. For example, a COVID-19 risk score, representing the totality of an individual's spatiotemporal exposures to COVID-19 infected/suspected cases and infectious environments, could be calculated on the basis of his/her fine-scale contact history. One such score could serve as important evidence of the infection status at COVID-19 test centers [11] and help to prevent false-positives from being isolated and false-negatives from going unnoticed. That is to say, an individual who has tested positive for SARS-CoV-2 and has had recent exposure to a COVID-19 risk is more likely to be a true positive, and quarantine should be considered.

On the contrary, an individual who has tested positive is likely to be a false-positive if lacking recent exposure to a COVID-19 risk. A short quarantine period may be
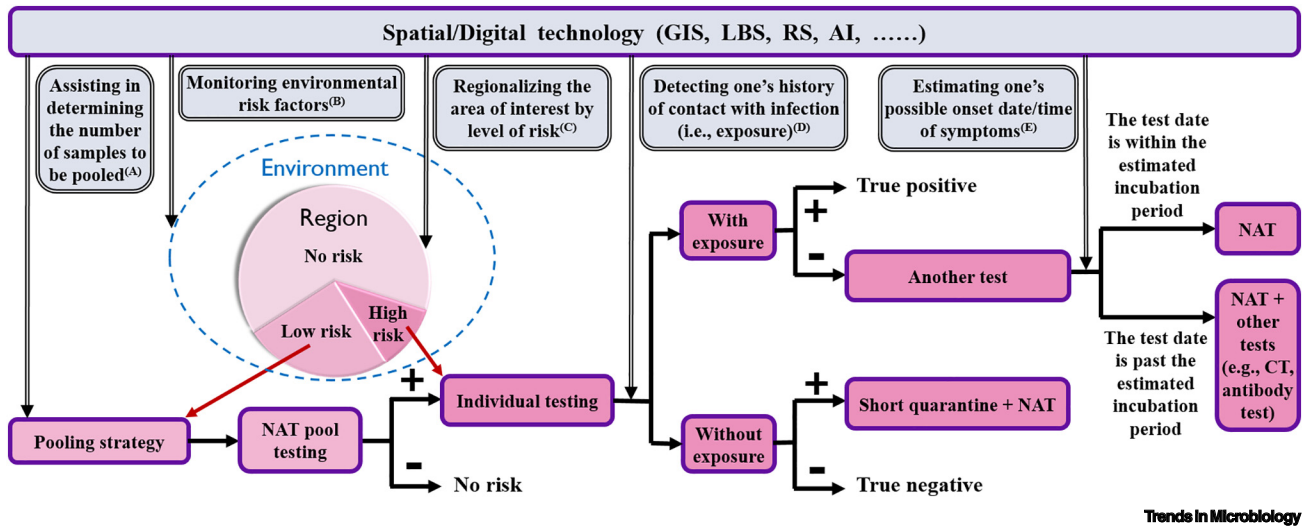
Figure 1. Spatial and digital technologies for assisting with traditional testing for SARS-CoV-2. Spatial/digital technologies could be incorporated into different stages of SARS-CoV-2 testing, and combined with traditional test methods, to improve the diagnostic accuracy of COVID-19 patients: (A) LBS+GIS+AI enable an estimation of the local potential prevalence of COVID-19 infection, to assist in determining the number of samples to be pooled in a pooling strategy; (B) RS enables monitoring environmental risk factors of COVID-19 transmission; (C) LBS+GIS+AI enable dividing a given area into regions with various levels of COVID-19 risk; (D) LBS+GIS+AI enable analyzing individual movement trajectories to detect one's history of contact with COVID-19 infection; (E) LBS+GIS+AI enable tracing an individual's history of movement and contact back to the date/time of contact with infection, to estimate the possible onset date/time of symptoms. Abbreviations: AI, artificial intelligence; COVID-19, coronavirus disease 2019; CT, computed tomography; GIS, Geographic Information Systems; LBS, location-based services; NAT, nucleic acid testing; RS, remote sensing; SARS-CoV-2, severe acute respiratory syndrome coronavirus 2.

needed in some situations, but further NAT with a different type of sample (e.g., nasopharyngeal swabs, oral pharyngeal swabs, or throat swabs) should follow. Similarly, an individual who tested negative for SARS-CoV-2 and has had no recent exposure to a COVID-19 risk is more likely to be a true negative. Conversely, an individual who tested negative but who has had recent exposure to a COVID-19 risk would require health professionals to select additional test method(s) to confirm the infection status. The selection of test methods should consider the exact time of an individual's exposure to a COVID-19 risk, and to what extent (i.e., the duration and intensity of the exposure); this enables an estimation of an individual's possible onset date (and time) of symptoms. That is to say, if the test date is within the estimated incubation period, the negative SARS-CoV-2 test result may imply an early-stage infecton; in this case, a short quarantine period may be needed and further NAT should follow. If the test date is past the estimated incubation period,

the negative SARS-CoV-2 test result may imply an asymptomatic patient during the recovery period, in which case a CT test may be needed to detect lesions or other subtle changes (e.g., lung parenchymal changes).

Economizing on the cost of large-scale interventions

The aforementioned COVID-19 risk score may also enable dividing the region of interest into communities with different levels of risk, which could substantially reduce the cost of large-scale interventions, for example, blanket testing, by providing precise guidance on the selection of test locations and methods. Communities without any historical trace of confirmed and suspected cases could be excluded from blanket testing. A sample pooling strategy, previously used for community monitoring of infectious diseases by mixing a preselected number of samples together in a batch, may be considered in low-risk communities where individuals do not have an exposure history but some present

with a COVID-19-like syndrome [12]. Individual testing is needed only if a given pool exhibits a positive result, so that the wastage of testing resources could be substantially reduced in those communities due to a low chance of COVID-19 infection. Moreover, the number of samples pooled in such strategies is usually determined by the local prevalence of COVID-19 on the basis of confirmed cases [13], which could be better estimated based on spatio-temporal exposures to COVID-19 risk of all the people in the community. In high-risk communities, it is still possible to differentiate low-risk and high-risk individuals on the basis of their contact history. NAT may be optimal for low-risk individuals, while CT may be more efficient for high-risk individuals due to the uncertain sensitivity of NAT.

Monitoring environmental risk factors of disease incidence

As COVID-19 transmission has extended from animal–human and human–human to environment–human, some other advanced spatial technologies, such as remote

sensing (i.e., earth observation), may also help to select sites of greatest need for detection and interventions [14]. They are especially useful when healthcare resources are limited during emergency events, and/or when an epidemic has become a pandemic. Remote sensing features a simultaneous data acquisition capacity over a large region, and also has a short revisit time (i.e., the time elapsed between two continuous observations of the same location by a satellite) for the majority of the Earth's landmasses. These unique advantages make it possible to monitor the environmental conditions supporting SARS-CoV-2 survival and COVID-19 transmission in real time, once the potential environmental determinants of the increasing cases are identified. For example, temporal increases in COVID-19 cases might be associated with short-term variations in ambient air pollution. Remote sensing possesses the capacity of acquiring air pollutant concentrations over a large region within a short time period (e.g., covering the whole of China within 2 hours and twice per day), which makes it possible to conduct a dynamic classification of regions with different levels of risk, and hence prioritize high-risk regions for interventions (e.g., conducting SARS-CoV-2 tests) [15].

Concluding remarks

Spatial and digital technologies in spatial lifecourse epidemiology would leverage fine-scale individual contact histories from multiple sources (e.g., population/syndromic surveillance systems, crowdsourced data, social networks) to provide additional objective evidence for determining the necessity of receiving traditional tests, and for assisting medical staff in interpreting test results of traditional methods including NAT. In the future, an individual's fine-scale contact histories are expected to be imported, and/or integrated with traditional test results, in artificial intelligence-based, portable decision-making systems, to improve the cost-effective use of testing resources and the diagnostic accuracy of COVID-19 patients. However, protecting individual confidentiality should be paramount when integrating spatial and digital methods with traditional test methods. Some frameworks and protocols with different levels of confidentiality protection have been developed during the COVID-19 pandemic, including decentralized privacy-preserving proximity tracing and pan-European privacy-preserving proximity tracing, which aim to minimize the risk of compromising the confidentiality in respect of individual infected patients while notifying others of their potential contact with those patients. All in all, these hybrid strategies, on the premise of fully protecting individual privacy, would significantly advance our capacity to curb epidemics as soon as possible, and better prepare us for entering a new era of high-impact and high-frequency epidemics [9].

Declaration of interests

There are no interests to declare.

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