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Coronavirus Pandemic

On the early detecting of the COVID-19 outbreak

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Abstract
Introduction: This paper aims to measure the performance of early detection methods, which are usually used for infectious diseases.
Methodology: By using real data of confirmed Coronavirus cases from the Kingdom of Saudi Arabia and Italy, the moving epidemic method (MEM) and the moving average cumulative sums (Mov. Avg Cusum) methods are used in our simulation study.
Results: Our results suggested that the CUSUM method outperforms the MEM in detecting the start of the Coronavirus outbreak.

Key words: Public health; COVID-19; monitoring; detection method; MEM; CUSUM.

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Introduction

In the 21st century, the world faces a ruthless epidemic, namely Coronavirus (COVID-19) which has spread around the world and taken many lives of people worldwide. The first appearance of the COVID-19 was in December 2019 in Wuhan City, Hubei Province of China. By March 2020, the World Health Organization (WHO) declared that the world faces a pandemic. Consequentially, many countries applied strict social distancing measures to reduce the virus spread. Capturing the propagation pattern of the disease then estimating its spread in the future helps the decision-makers' to take suitable actions that save lives and at the same time minimize pandemic consequences.

Various mathematical and statistical models that used the COVID-19 data can be found in the literature. For example, Ekum and Ogunsanya [1] applied polynomial models to COVID-19 global data and suggested that and the best model they have studied to predict the spread of COVID-19 globally was the cubic model with a constant term. Adeniyi *et al*. [2] applied a non-linear mathematical model on COVID-19 data of Italy to investigate the effect of healthy sanitation and awareness on the transmission dynamics of COVID-19 prevalence. Alshammari [3] proposed a susceptible-exposed-symptomatic- asymptomatic -hospitalized-recovered (SEYNHR) dynamical model to investigate the transmission of COVID-19 in Saudi Arabia, his estimation of the basic reproduction number was about 2.7.

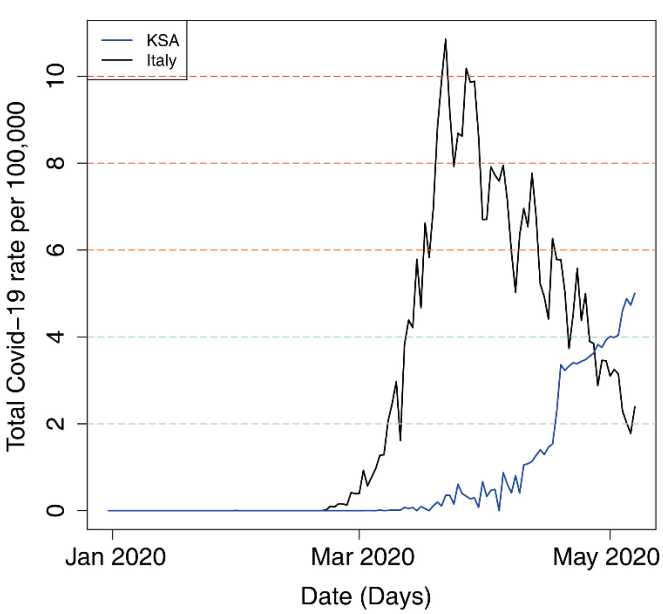
One of the most popular methods in early detection systems for infectious diseases is the Moving Epidemic Method (MEM). It is one of the ways recently used to monitor influenza and to launch early warning to minimize human losses from the disease [4,5]. The MEM uses historical data (at least 5 years) and aims to calculate the minimum number of weeks with the maximum cumulative rate. Then, the remaining weekly rates before and after this period are assumed to be pre- and post-epidemic, respectively. The MEM considers the upper limit of the 95% confidence interval of the geometric mean of the pre-epidemic rates as the pre-epidemic threshold. If the pre-epidemic threshold is breached, then the MEM classifies the intensity of activity (as “low”, “medium”, “high” and “very high”) according to the MEM designated cut-off points. Also, the post-epidemic thresholds are calculated by the same technique.

There is rich literature on the use of the MEM for detecting the start of influenza activity. For instance, the European Centre for Disease Prevention and Control (ECDC) considered the MEM as a standardized approach for the Influenza-Like Illness (ILI) reporting for the 2011/2012 influenza season in Spain [6]. Some recent researches have been using the MEM method in different health institutions to detect influenza outbreaks in different places such as Spain [6], Europe [4], United Kingdom [7,8], United States [9], Cambodia [10], Portugal [11], France [12] and Scotland [13].

Another popular method in early detection systems for infectious diseases is the Moving Average Cumulative sums (Mov. Avg Cusum) method [14], which has become widely used in different health institutions in different countries. Given a series of observations $y_t = 1,2, \ldots$ with the $d - day$ upper CUSUM at time t (which is donated by C_t^+), then the CUSUM method raises an alarm if $C_t^{+\phi_{\left(1-\frac{\alpha}{2}\right)}}$, where $\phi$is a standard Normal deviate. This value represents the pre-specified threshold proposed to control the alarm.

Many studies used the CUSUM method to detect the right alarm for infectious diseases such as influenza. For example, Woodall *et al*. [15] showed that the use of the CUSUM method chart approach outperformed the scan statistics, and this conclusion is also found by Han *et al*. [16]. Furthermore, Xu *et al*. [17] used the CUSUM method to detect ten school influenza outbreaks in the period from September 2012 to December 2014 and concluded that the early intervention had high effectiveness. Australia [18] applied two different types of CUSUM-based automated monitoring algorithms, namely the three Early Aberration Reporting System (EARS) CUSUM and the negative binomial CUSUM, to identify outbreaks of Ross River virus (RRv) disease in Western Australia between the years 1991 and 2004.

Figure 1. Confirmed COVID-19 cases per 100,000 populations in Saudi Arabia and Italy.



The study suggested that the negative binomial CUSUM had a significantly greater ability to identify outbreaks of RRv disease.

Methodology

In this section, we briefly outline the methods used in our study to detect the start of an epidemic outbreak, namely the CUSUM method and the MEM.

Cumulative Summation (CUSUM) Method

Let $y_t = 1,2, \ldots$ be a series of observations. Then the upper CUSUM limit over a $d - day$ period can be defined at time t as:

$$C_t^{+max}$$

with C_{t-d}^{+0} [19,20]. The parameter k gives the lowest standardized difference from the operating mean to be ignored by the system. The operation mean $\bar{y}_{(7)}$ and the operation variance $S^2_{(7)}$ are calculated from the seven days series $y_{t-d-7}, \ldots, y_{t-d-1}$ prior to the most recent d days. The value of $\Phi_{\left(\frac{1-\alpha}{2}\right)}$ is the pre-specified threshold used to control the alarm, where Φ is a standard Normal deviate (z value). When C_t^+ value surpasses the identified threshold, the alarm will be raised [20].

The Moving Epidemic Method (MEM)

The MEM searches for the optimum epidemic point by starting with one day and seeing how many cases represent the total epidemic. The one-day period is chosen by maximizing the number of cases that a period can contain that is, reaching the peak. The one-day period, which contains the most cases is the period that contains the peak. If the one-day period has, say, 50 cases and the total number of cases in that season is 500, then the one-day period represents 10% of the total (50/500). Then we add one more day to form the two-day period and repeat the process until we find the two-day period that contains the highest number of cases (probably the peak and a neighbor). If that period has, say 100 cases, then it represents 20% of cases. So adding one day (from one to two) we have gained 10% (from 10% to 20%).

Simulation Study

Figure 1 represents COVID-19 daily cases per 100,000 populations in Saudi Arabia and Italy while Table 1 shows the statistical summary of the data.

Our simulation study aims to compare the performance of two early detection methods systems with 2020 pandemic data in Saudi Arabia and Italy. In both countries, we applied daily confirmed the number

Table 1. Summary of COVID-19 rates and cumulative sum (per 100,000) in Italy and Saudi Arabia.

COVID-19	Rates		Cumulative sum	
Country	**Italy**	**Saudi Arabia**	**Italy**	**Saudi Arabia**
Minimum	0.0000	0.0000	0.5005	0.0000
1st Quartile	0.1092	0.0000	0.2586	0.0000
Median	3.3524	0.0861	63.5121	0.6068
Mean	3.6219	0.9671	125.1151	13.3641
3rd Quartile	6.3282	1.2381	257.1003	12.9221
Maximum	10.8524	5.0059	354.9437	94.7715
S.D.	3.2831	1.5115	132.8653	23.9403

of cases from 31th Dec 2019 to 7th May 2020 (data taken from the European Centre for Disease Prevention and Control [21]). It should be clarified that the MEM requires at least 5 years of historical data, and we assumed that the five-year historical data has a very small (around zero) number of cases (as suggested by other study [5]). Different baselines can be considered in the simulation, we used a Poisson distribution (with daily means that obtained from the real data) to simulate 100 cases to determine the exact day of the alarm.

Results and Discussion

Our results indicate that the CUSUM method with the 100 simulated cases raise the alarms in Italy on 23rd of February 2020, while the alarms are raised in Saudi Arabia in the period 6th-11th of March 2020 (Figure 2). On the other hand, the MEM fails to raise any alarm in both countries as presented in Figure 3. The missing historical data could be the cause of the failure of the MEM to raise any alarm.

Table 2 reports an overview of Italian and Saudi governments' actions to control COVID-19 [22]. From Table 2, it can be seen that Italy in general was late in its response. For example, the schools and universities were closed on the 8th of March 2020, which can be considered as a delayed-action with the given 100 alarms on the 23rd of February 2020. This delay could be one of the reasons that caused major difficulty for the health system in Italy to manage the COVID-19 pandemic. Regarding Saudi Arabia, a very short delay (only two days of delay) between the first alarm on the 6th of March 2020 and the first action, which was on the 8th of March 2020. The early response in Saudi Arabia could be one of the reasons that caused the lower mean of the daily cases cumulative sum compared to Italy (Table 1).

Conclusions

In this paper, we compared the performance of the CUSUM method and MEM in detecting the start of the

Figure 2. Confirmed cumulative sum of cases per 100,000 populations in Saudi Arabia and Italy. Dotted vertical lines represent the alert day in each country.

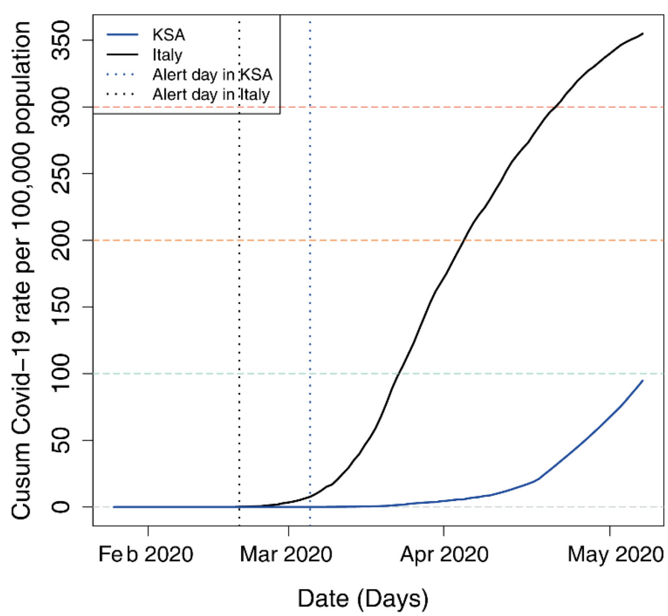


Figure 3. The CUSUM performance with 100 simulated cases (**A** Italy and **B** Saudi Arabia), in addition to the MEM modeling with 100 simulated cases (**C** Italy and **D** Saudi Arabia).

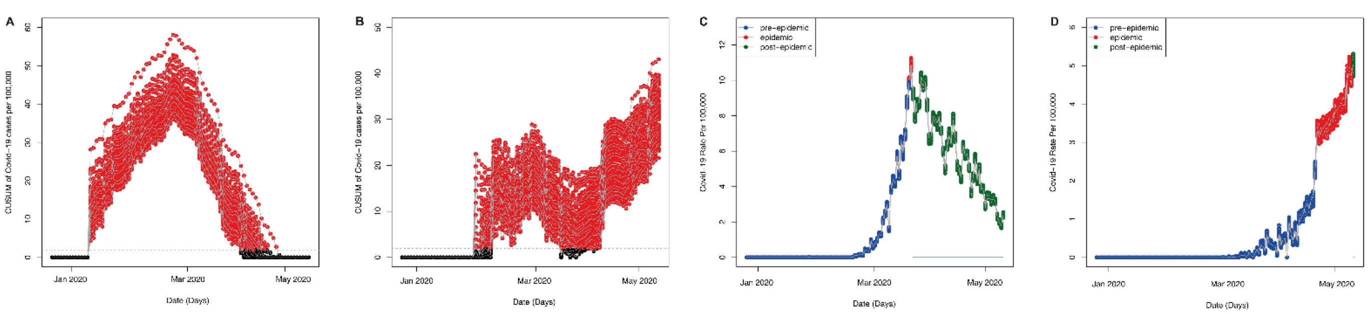


Table 2. Overview of Italian and Saudi governments' actions to control COVID-19 since the appearance of the first case. Time lag represents the gap (in days) between the action and raising the first alarm found in our results.

Country/ Suggested alarm date	Action	Date	Case per 100,000 population	Time lag
Italy/ 23rd of February 2020)	Reporting the first case	31st January 2020	0.004965	NA
	Closing schools and universities	8th March 2020	9.736842	-14 days
	Extending the lockdown nationwide	9th March 2020	12.20622	-15 days
Saudi Arabia/ 6th-11th of March 2020)	Reporting the first case	2nd March 2020	0.002967	NA
	Closing schools and universities	8th March 2020	0.020772	-2 days
	Extending the lockdown nationwide	8th March 2020	0.020772	-2 days

Coronavirus outbreak in two countries, namely the Kingdom of Saudi Arabia and Italy. Based on the given data, our results strongly suggested the success of the CUSUM method in determining the start of the Coronavirus outbreak in the two countries, while the MEM failed to raise any alarm. The Coronavirus can be considered as the first pandemic in the 21st century, and more empirical studies in detecting the start of a pandemic outbreak should be conducted to help health systems to face any future pandemics.

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