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JIPH-816; No. of Pages 4

ARTICLE IN PRESS

Journal of Infection and Public Health xxx (2017) xxx–xxx

Contents lists available at ScienceDirect

Journal of Infection and Public Health

journal homepage: http://www.elsevier.com/locate/jiph

Timely detection of influenza outbreaks in Iran: Evaluating the performance of the exponentially weighted moving average

Manoochehr Solgi [a], Manoochehr Karami [a,b,*], Jalal Poorolajal [a,c]

[a] Department of Epidemiology, School of Public Health, Hamadan University of Medical Sciences, Hamadan, Iran
[b] Social Determinants of Health Research Center, Hamadan University of Medical Sciences, Hamadan, Iran
[c] Modeling of Noncommunicable Diseases Research Center, Hamadan University of Medical Sciences, Hamadan, Iran

ARTICLE INFO

Article history:
Received 9 June 2017
Received in revised form 8 August 2017
Accepted 9 September 2017

Keywords:
Public health surveillance
Syndromic surveillance
Exponentially Weighted Moving Average
Influenza
Outbreak
Iran

ABSTRACT

Background: Real time detection of influenza outbreaks is necessary by public health authorities. The aim of this study was to determine the performance of the Exponentially Weighted Moving Average (EWMA) in detection of influenza outbreaks in Iran from January 2010 to December 2015.

Methods: The EWMA algorithms were applied to weekly counts of suspected cases of influenza (influenza-like illnesses) to detect real outbreaks which have occurred in Iran from January 2010 to December 2015. The performance of EWMA algorithms was measured using sensitivity, specificity, false alarm rate, likelihood ratios and area under the receiver operating characteristics (ROC) curve.

Results: Sensitivity of the EWMA for all of occurred outbreaks from 2010 to 2015 was 40% (95% CI: 29%, 50%). The corresponding value of detection of occurred outbreaks in 2010, 2011, 2013, 2014 and 2015 were 50%, 100%, 76%, 64% and 100% respectively. Among different algorithms, EWMA with $\lambda = 0.5$ had the best performance (area under the Curve = 100%) for the detection of occurred outbreaks in 2011.

Conclusions: Our findings revealed that the performance of the EWMA in the real time detection influenza outbreak in Iran is appropriate. However, public health surveillance systems need to use different outbreak detection methods for detecting aberrations in influenza-like illnesses activity.

Introduction

Influenza like illness (ILI) or acute respiratory infections can cause several types of viral and bacterial respiratory infections in humans. ILI was defined as "*a sudden onset fever over than* 38 °C *and cough, associated or not with other symptoms such as breathing difficulty, headache, etc.*" [1]. Influenza caused morbidity and mortality throughout the world, including Iran. According to the World Health Organization, each year 5–10% of adults and 20–30% of children are diagnosed with influenza virus which causes 3–5 million severe illnesses causing 250,000–500,000 deaths around the world [2]. Influenza viruses cause epidemics and pandemics. Moreover, it causes outbreaks and epidemics fast which results in the hospitalization of a large number of susceptible people, especially children and the elderly and economic difficulties imposed on society, resulting in absence from work and school [3].

There are different outbreak detection methods and statistical methods for detecting aberrations in ILI activity, including Cumulative Sum (CUSUM), Exponentially Weighted Moving Average (EWMA) and time series models [4]. ILI as a proxy of influenza activity and influenza related outbreaks occurrence has been used by surveillance systems of influenza worldwide. World health Organization has developed a web based tool, FluNet, to monitoring influenza activity (http://www.who.int/influenza/gisrs_laboratory/flunet/en). One of the most known methods and algorithms used by the influenza surveillance systems to detect outbreaks or any change in the ILI activity is EWMA. EWMA is a group-based method of statistical process control and efficiency in detecting small changes [5–8].

Early response to health events, especially public health emergency with international concern are a major public health priority. Outbreak detection methods and algorithms as the main tools for public health surveillance systems are under the umbrella of temporal and spatial methods. There are three different approaches which might be used by syndromic surveillance systems to address

* Corresponding author at: Fahmide St Department of Epidemiology, School of Public Health, Hamadan University of Medical Sciences, Hamadan, 65178-3-8736, Iran.
E-mail address: Iran.ma.karami@umsha.ac.ir (M. Karami).

http://dx.doi.org/10.1016/j.jiph.2017.09.011
1876-0341/

Please cite this article in press as: Solgi M, et al. Timely detection of influenza outbreaks in Iran: Evaluating the performance of the exponentially weighted moving average. J Infect Public Health (2017), http://dx.doi.org/10.1016/j.jiph.2017.09.011

Table 1
Characteristics of the used algorithms in the study according to fixed Parameter and time period.

Algorithm no.	Algorithm	k(fixed parameter)
Algorithm 1	EWMA ($\lambda = 0.1$)	2
Algorithm 2	EWMA ($\lambda = 0.2$)	2
Algorithm 3	EWMA ($\lambda = 0.3$)	2
Algorithm 4	EWMA ($\lambda = 0.4$)	2
Algorithm 5	EWMA ($\lambda = 0.5$)	2
Algorithm 6	EWMA ($\lambda = 0.6$)	2
Algorithm 7	EWMA ($\lambda = 0.7$)	2
Algorithm 8	EWMA ($\lambda = 0.8$)	2
Algorithm 9	EWMA ($\lambda = 0.9$)	2

the performances of outbreak detection algorithms, including the real data testing, fully synthetic simulation and semi-synthetic simulation. The real data testing approach provides the highest degree of validity in comparison to other evaluation methods [9].

Timely detection of influenza outbreaks is necessary by public health surveillance systems. Moreover, few published studies addressed the performance of statistical methods in influenza surveillance, especially in Iran. This study aimed to address the performance of EWMA in detection of influenza outbreaks in Iran from January 2010 to December 2015.

Material and methods

Data

The data of all registered cases of ILI in Iran were obtained from FluNet web base tool, World Health Organization from January 2010 to December 2015 (http://www.who.int/influenza/gisrs_laboratory/flunet/en). In addition, the status of ILI activity, including outbreak activity was obtained from FluNet and considered as the gold standard of influenza outbreak occurrence. We enrolled aggregate data of 53,526 ILI cases with fever more than 38° C and cough that it was started within seven days. EWMA was applied to weekly reported counts of suspected cases of ILI to detect occurred outbreaks during the study period in Iran.

Outbreak detection method

EWMA statistics are defined by the following recursive equation [10]:

$$EWMA_t = \lambda Y_t + (1 - \lambda) EWMA_{t-1}. \quad (1)$$

Where, Y_t equals the number of suspected cases of influenza in weekly t, λ is the weighting parameter that has been considered as 0.1 for $EWMA_1$, 0.2 for $EWMA_2$ and so on (Table 1). Details on fine-tuning approach on weighting parameters, calculating the $EWMA_t$ statistic and estimation of the upper control limit of EWMA were described elsewhere [6,10].

Measures of algorithm's performance

The performance of EWMA algorithms according to different years of the study period in detection of ILI outbreaks was measured using sensitivity, specificity, false alarm rate, likelihood ratios and area under the receiver operating characteristics (ROC) curve (AUC). Total number of outbreak-weeks (80 outbreak-weeks) was considered as the gold standard to calculate appropriate measures to evaluate performance of algorithms. Accordingly, the denominator for sensitivity and specificity formulas was 80 outbreak days and 233 non-outbreak days, respectively. AUC with 95% confidence intervals (95% CI) was used to compare different algorithms and greater values indicate better performance. Briefly, greater values of AUC, i.e. AUC = 1 OR = 100%, indicate better performance of a specific EWMA algorithm in comparison to other algorithms. AUC values have been reported by percentage throughout text and displayed in Figures.

Descriptive statistics including mean, standard deviation (SD), and measures of performance except ROC were calculated using Microsoft Excel version 2010. ROC curve plotted using the Stata software version 11.

Results

Overall Sensitivity of the EWMA for all occurred outbreaks from 2010 to 2015 was 40% (95% CI: 29%, 50%). The corresponding values of detection of occurred outbreaks in 2010, 2011, 2013, 2014 and 2015 were 50%, 100%, 76%, 64% and 100%, respectively. Among different algorithms, EWMA with $\lambda = 0.5$ had the best performance (sensitivity = 100%) in detecting occurred outbreaks in 2015. Tables 2 and 3 show disaggregated measures of EWMA performance by different values of λ parameter entitled $EWMA_1$ to $EWMA_9$ including sensitivity, specificity, false alarm rate, false negative rate, positive and negative likelihood ratios.

In total, the AUC of the EWMA for all of occurred outbreaks from 2010 to 2015 was 94%. Same values according to different λ parameter for $EWMA_1$ to $EWMA_9$ are shown in Fig. 1. The corresponding value of AUC for detection of occurred outbreaks in 2010, 2011, 2013, 2014 and 2015 were 92%, 100%, 95%, 91% and 100%, respectively. Among different algorithms, EWMA with $\lambda = 0.5$ had the best performance (AUC = 100%) for the detection of occurred outbreaks in 2011 (Fig. 2).

The false alarm rate of the EWMA for all of occurred outbreaks from 2010 to 2015 was 2% (95% CI: 1%, 3%). The corresponding values for detection of occurred outbreaks in 2010, 2011, 2013, 2014 and 2015 were 8%, 5%, 3%, zero and 5%, respectively. Among different algorithms, EWMA with $\lambda = 0.3$ had the best performance (false alarm rate = 2%) to the detection of occurred outbreaks in 2011.

Positive likelihood ratio of the EWMA for all of occurred outbreaks from 2010 to 2015 was 20. The corresponding values for detection of occurred outbreaks in 2010, 2011, 2013, 2014 and 2015 were 6.25, 13, 25.33, 8.60 and 20, respectively. Among different

Table 2
Sensitivity, specificity, false alarm rate, false negative rate, positive and negative likelihood ratios of the EWMA algorithms during study period (2010–2015).

Algorithm	Period	Sensitivity	Specificity	False alarm rate	False negative rate	Positive likelihood ratio	Negative likelihood ratio
EWMA ($\lambda = 0.1$)	2010–2015	13(5–20)[a]	100	0	87(80–95)	0	0.87
EWMA ($\lambda = 0.2$)	2010–2015	24(14–33)	97(95–99)	3(2–4)	76(67–86)	8	0.78
EWMA ($\lambda = 0.3$)	2010–2015	31(21–41)	97(95–99)	3(2–4)	69(59–79)	10.33	0.71
EWMA ($\lambda = 0.4$)	2010–2015	33(22–43)	98(96–93)	2(1–3)	67(57–78)	16.50	0.69
EWMA ($\lambda = 0.5$)	2010–2015	36(26–46)	98(96–93)	2(1–3)	64(54–74)	18	0.65
EWMA ($\lambda = 0.6$)	2010–2015	38(28–49)	97(95–99)	3(2–4)	62(51–72)	12.66	0.63
EWMA ($\lambda = 0.7$)	2010–2015	40(29–50)	98(96–93)	2(1–3)	60(50–71)	20	0.62
EWMA ($\lambda = 0.8$)	2010–2015	38(28–49)	97(95–99)	3(2–4)	62(51–72)	12.66	0.64
EWMA ($\lambda = 0.9$)	2010–2015	36(26–46)	98(96–93)	2(1–3)	64(54–74)	18	0.66

[a] Numbers in parenthesis indicate 95% confidence intervals around the point estimate.

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