An Efficient Burst Transmission Scheme for Wireless Sensor Networks

Zeeshan Ansar, Jianjun Wen, Eyuel Debebe Ayele, Waltenegus Dargie
Chair for Computer Networks, Faculty of Computer Science, Technical University of Dresden
01062 Dresden, Germany
{zeeshan.ansar, jianjun.wen, eyuel.ayele, waltenegus.dargie}@tu-dresden.de

ABSTRACT

This paper addresses link quality fluctuation and its impact on the packet delivery capacity of wireless sensor networks. Independent studies have previously confirmed that link quality fluctuates even in a static deployment and understanding stable durations, good and bad alike, can contribute to the efficient transmission of packets. We propose a two stage Markov model to characterise link quality fluctuation and to determine when and for how long nodes should transmit packets in burst. Both to develop and test our model, we deployed a wireless sensor network consisting of 14 nodes in a garden and transmitted more than 120,000 packets with different links. The experiment results confirm that our approach improved the packet delivery capacity of the links by up to 40% when compared with a baseline and by up to 25% when compared with a scheme that employs conditional distribution functions.

Keywords

Burst transmission; link quality estimation; link quality fluctuation; wireless link

1. INTRODUCTION

In many wireless sensor networks the nodes are deployed on the objects or embedded into the processes they monitor, which considerably influence the quality of communication between nodes. For example, in structural health monitoring, the oscillation of a bridge, in water quality monitoring, the water and the movement of water, in healthcare applications the movement of people, in precision agriculture the movement and the shadow of plants affect the quality of an established link. Fluctuation of link quality in turn has a negative impact on successful packet delivery for applications which require high goodput and for most relay nodes which should aggregate and forward packets towards a base station. Furthermore, repeated retransmission of lost packets increases not only latency at all levels of communication but also energy consumption which may reduce the lifetime of the entire network. Hence, efficient transmission schemes that take channel characteristics (statistics) into account are critical to improve the reliability and lifetime of the networks.

MSWiM'15 November 02-06, 2015, Cancun, Mexico
© 2015 ACM.ISBN 978-1-4503-3762-5/15/11...$15.00
DOI: http://dx.doi.org/10.1145/2811587.2811622

At present, the duty of dealing with link quality fluctuation mainly rests on the physical layer components, which employ strategies such as dynamic rate adaptation, dynamic channel allocation, or dynamic transmission power adjustment to maintain link quality. These strategies, however, have a limited scope because they can deal only with short-term fluctuations. For example, a node may increase its transmission power to deal with link quality fluctuation; by doing so, however, it affects other nearby nodes which may also increase their transmission power to deal with the new change. The same can be said of dynamic channel allocation. To the best of our knowledge, existing transceivers complying with the IEEE 802.15.4 do not support dynamic rate adaptation. Alternatively, the MAC layer can deal with link quality fluctuation by providing efficient packet transmission schemes that have middle- to long-term scope. One of these schemes can be *burst transmission*, even though it was first proposed to address a different concern, namely, achieving high throughput [2]. The idea is as follows: Instead of making nodes compete for winning a channel for each packet they transmit (as is done with IEEE 802.11 and IEEE 802.15.4 contention-based medium access specifications), nodes are permitted to transmit multiple packets in burst once they win a medium. This scheme disregards short-term fairness but experiment results suggest that it can significantly increase overall network throughput. This same approach can be used to deal with link quality fluctuation. Since wireless sensor networks are deployed for a long time, sufficient statistics can be collected to reason about channel characteristics and from this statistics, it is possible to determine the probability of successfully transmitting n number of packets in succession.

In this paper we propose a two-stage Markov model to deal with link quality fluctuations. The model first classifies link quality into different clusters (or states) and determines the transition probability between the states. Secondly, it estimate the average duration of a link staying in a state and the optimal number of packets that can be transmitted in this state. As a summary, the contributions of the paper are the following: (1) Using data collected from our sensor network, we study the temporal characteristic of channel state variations. (2) Using discrete Markov models, we establish a relationship between a state and the optimal number of packets that can be transmitted in burst. (3) We quantitatively compare the throughput of our model with two approaches, namely, (a) a baseline burst transmission in which no scheme is used to determine the number of packets that should be transmitted in succession and (b) a previous approach which uses Bayesian Estimation [10] to determine the optimal burst size. The rest of this paper is organized as follows: In Section 2, we review work on link quality fluctuation and link quality characterisation in detail. In Section 3, we introduce our approach and the three steps required to develop our transmission scheme. In Section 4, we provide quantitative evaluation of our model and compare it with existing approaches. Finally in Section 5, we provide concluding remarks and future work.

2. RELATED WORK

Link quality fluctuation and its impact on the energy-efficiency and the quality of service of wireless sensor networks is an active research area, particularly in the context of 802.15.4 standard. Different approaches and metrics have been employed to characterise the quality of wireless links. Experimental observations suggest that link quality can be broadly categorised into perfect, intermediate, or poor. They also suggest that it exhibits bursty characteristic [9]. Dealing or copping with these aspects is of paramount importance to deploy and use reliable networks. One approach adopted by the research community is setting in place packet transmission schemes at the MAC layer which take knowledge of link quality fluctuation into consideration. In [6], the authors use the SNR values of RTS/CTS control messages to learn about the current state of a link and to decide whether data packets should be transmitted or withheld. The decision is made by employing a Markov decision process (MDP). In [3], the authors propose cooperative communication between sensor nodes to take advantage of diversity gain to overcome the effect of fading channels. Liu et al. [4] propose a data transmission algorithm that uses a Hidden Markov Model. It delays packet transmissions to overcome periods of poor channel quality and high interference while ensuring that the throughput requirement of an application is met. Srinivasan et al. [9] propose a β metric to compute the burstiness of a link. The β factor of a link is a measure of approximation to an ideal link. A value of $\beta = 1$ and $\beta = 0$ represents a perfectly correlated link and an uncorrelated link, respectively. The β metric is calculated by evaluating the distance between a conditional probability delivery function (CPDF) of a given link and an ideal link. The CPDF is a measure of the probability of successful reception of the next packet after n consecutive successes or failures. The authors propose a transmission control scheme as a performance measure of the β metric. This scheme is intended to increase the packet reception ratio by transmitting packets in bursts until a failure is encountered. When a failure occurs, transmission is halted for 500 ms. The limitation of this approach is the requirement of a large amount of data to predict the success of the next packet. Wen et al. [10] propose an offline scheme that uses the conditional probability distribution function of SNR fluctuation to estimate the expected consecutive success and consecutive failure of packet transmission and to adapt the number of packets that can be transmitted in burst followed by a period of pause.

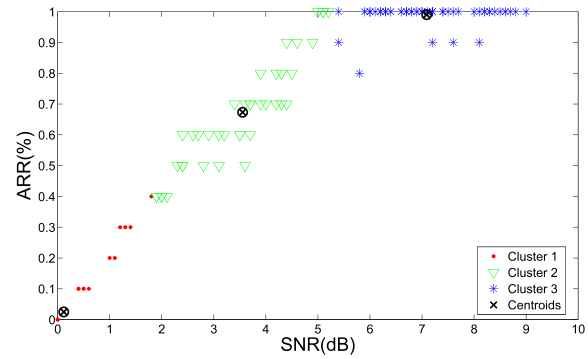

Figure 1: A summary of relationship between the SNR and ARR of a wireless link. SNR is computed as the difference between RSSI and background noise power.

In contrast to the proposed approaches, we aim to provide a middle- to long-term solution for dealing with link quality fluctuation. Our approach extends the idea of burst transmission both to increase network throughput and to gather sufficient statistics pertaining to link quality fluctuation and to use this knowledge for determining when and for how long nodes should transmit packet in burst.

3. LINK QUALITY MODEL

Most existing off-the-shelf transceivers make link quality indicator metrics available to higher layer services including received signal strength indicator (RSSI), link quality indicator (LQI), and background noise level. Unfortunately, it is not possible to establish deterministic relationships between these metrics and successful packet delivery. Packets can be successfully transmitted with a certain probability even when the metrics indicate that the link is bad; and lost even when they indicate that it is good. One of the metrics used to characterise link quality fluctuation is Acknowledgement Reception Ratio (ARR), which summarises the relationship between successful packet delivery and signal-to-noise ratio (SNR). The metric is computed as follows: First, a sequence of packets are divided into a set of subsequence. Each subsequence is transmitted in succession and each packet in a subsequence is acknowledged when it is successfully received. Then for that subsequence, the ARR is the ratio of the number of successfully received acknowledgement packets to the total number of transmitted packets. The SNR of that subsequence is the average of the successfully received ACK packets. Likewise, all the set of subsequence is transmitted, the ARR is produced for each subsequence, and the corresponding SNR is computed. Then a 2-dimensional graph of ARR vs. SNR is plotted to summarise the relationship between the two quantities (as shown in Figure 1). The merit of this approach is that the quality of a link can be evaluated independent of the distance of separation between the transmitter and the receiver and physical layer parameters such as the transmission power and the specific channel allocated. The weakness of the approach is that for a short duration, the channel's characteristic is assumed to be both symmetrical and correlated to account for the SNR of lost packets. We adopt this approach to evaluate the effect of link quality fluctuation on successful packet delivery.

3.1 Clustering

In most practical settings, the quality of a link does not stay at a certain level for so long; instead it fluctuates between different levels. For tractability, these levels can be categorised into a few countable and non-overlapping regions and the average ARR of these regions can be considered to characterise link quality. Previously, different authors have classified these regions into good ($ARR \approx 1$), intermediate ($0.9 \leq ARR \leq 0.1$) and poor ($ARR < 0.1$) states [1, 9]. However, a strict classification of link quality into fixed regions is not realistic, because physical links have individual characteristics. Unlike previous approaches, we use K-mean clustering to determine the optimal number of clusters that best describe the distinct states of a link.

For $n >> 1$, let A_n be a discrete sequence of successfully acknowledged (1) and lost (0) packets. From this sequence, it is possible to establish the (ARR, SNR) pairs for this sequence. For example, Figure 1 displays the (ARR, SNR) distribution for one of the links we considered in our experiment (of which we shall give a detail account in Section 4). The K-mean clustering algorithm [5] can be applied on this vector with the goal of partitioning it into k mutually independent clusters, each cluster with its centroid representing a link quality state. The K-means treats each value of (ARR, SNR) pair as an object. Hence, similar objects are located close to each other, thus forming a cluster. To determine the optimal number of clusters for a given link, we employed the *silhouette method* [8], which iteratively compares the average distance between points within a cluster and across clusters to determine the number of clusters that can distinctly categorise a dataset. We begin with 2 clusters and increase the number of clusters until we obtain an optimal measure of distinctness.

3.2 State Transition Probabilities

After clustering, the next step is determining the probability of transitions between the clusters (signifying link quality fluctuation) during a continuous transmission of packets. This can be done using a first order Markov chain [7]. In this approach, time is divided into discrete slots and packets are transmitted in burst in each slot (for our case, we set the burst size to 10). Using the acknowledgement packets in each slot, the ARR, the average SNR, and the link quality state (cluster) are determined as discussed above. After a sufficiently large number of packets are transmitted and the ARR, SNR, and link quality state of subsequent slots are estimated likewise, the fluctuation in link quality is described by a state transition probability, which is computed as follows:

$$a_{ij} = P\left(S_j | S_i\right) = \frac{N_{i \to j}}{\sum_{m=1}^{M} N_{i \to m}} \tag{1}$$

where M is the total number of states and N is the number of transitions. An interesting aspect of Equation 1 is the possibility of asking (and answering) the following question: Given the channel is in a known state in the beginning of slot τ, what is the probability that it stays in the same state for the next d slots (as expressed by Equation 1). This is an important question because it directly addresses the question of link stability.

$$o = \left\{ \begin{matrix} S_n, & S_n, & S_n & \ldots\ldots & S_n, & S_m \\ 1 & 2 & 3 & & d & d+1 \end{matrix} \neq S_n \right\} \tag{2}$$

The question can be answered using the following expression:

$$P_n\left(d\right) = \left(a_{nn}\right)^d \left(1 - a_{nn}\right) \tag{3}$$

Where a_{nn} is the probability that the link quality is in state n and remains in the same state in the next time slot. Note that the plot of $P_n(d)$ for all d gives the probability mass function for state n, from which it is possible to determine the expected number of slots the link quality stays in state n:

$$\bar{d_n} = \sum_{d=1}^{\infty} d P_n\left(d\right) = \frac{1}{1 - a_{nn}} \tag{4}$$

3.3 Slot Scheduling

The long-term link quality fluctuation can be estimated using Equations 1 and 4. In the beginning c packets are transmitted in burst and based on the ARR of that slot, the state of the link quality is estimated. Then using Equation 4, the expected number of slots in which the link quality remains in the same state is estimated. Once the expected number of slots are utilised, the next state is estimated using Equation 1 and then the same process is repeated all over again. This approach however has two limitations. Firstly, because the transition between states is a probabilistic quantity, the approach will always choose the transition with the highest probability. However, a state transition with a low probability does not mean the transition does not occur. Secondly, once a wrong transition is chosen, the subsequent $\bar{d_n}$ slots computed by Equation 4 for that state do not reflect the actual link quality state. To deal with these problems we introduced two correction factors. Firstly, to correct the error that occurs due to wrong transitions, the transmission schemes takes periodic measurement and reestimate the channel states; if there is a discrepancy between the latest estimated state and the state determined by the transition probability, then the latest state is taken as the present channel state. Secondly, to enable transition into states with low transition probabilities, we randomised the transition process as follows: $randomselect\left(S, A\right)$, where $S = (S_j, S_k, ..., S_n)$ and $A = (a_{ij}, a_{ik}, ..., a_{in})$.

3.4 Burst Size Determination

After the state sequence is determined, the next step is determining the number of packets that should be transmitted in burst in each state. The goal is minimising the number of lost packets. Once again we employ a first order Markov chain for this step but this time we fix the number of states to two, success (1) and failure (0). The sequence of received acknowledgement packets during a test phase is used to determine the state transition probabilities. Consider Figure 2 in which after 10 packets are transmitted in burst, the sequence of acknowledgement packets is given. From the sequence of acknowledgement packets, it can be seen that there are altogether 9 transitions: once from 0 to 0, twice from 0 to 1, twice from 1 to 0 and four times from 1 to 1. Hence the state transitions probabilities, in respective order, are: $a_{00} = \frac{1}{9}, a_{01} = \frac{2}{9}, a_{10} = \frac{2}{9}, a_{11} = \frac{4}{9}$. Once the state transition probabilities are determined, the expected number of burst size can be calculated once again by applying Equation 4. It must be noted that the sequence obtained in Figure 2 is not sufficient to produce reliable statistics. In reality, repeated experiments are conducted to obtain the state transition probabilities.

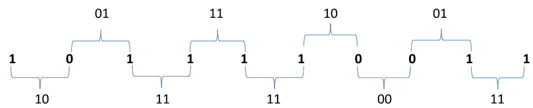

Figure 2: Sequence of acknowledgement packets signifying successful or failed packets transmission and the determination of state transition probabilities.

Table 1: A summary of physical land link layer parameters used to establish 6 links.

	link1	link2	link3	link4	link5	link6
Nodes	(2,11)	(4,9)	(2,12)	(3,7)	(5,10)	(1,4)
d (m)	27	19	35	8	23	15
p (dBm)	-10	-3	-15	-3	-15	-10

4. EVALUATION

To gather statistics pertaining to link quality fluctuation and to evaluate our scheme, we deployed a wireless sensor network consisting of 14 TelosB sensor nodes in a garden (Figure 3). The distance between the nodes was chosen arbitrarily and varied from 8 to 35 m. The nodes established direct links with each other to communicate packets. We selected 6 of these links and transmitted more than 120,000 packets. Table 1 summarises the links we selected for our evaluation and the transmission parameters for each link. Figure 4 displays the packet loss for all the links during a burst transmission of 2000 packets, to demonstrates how link quality fluctuation of even a static deployment impacts packet delivery (packet loss varied between 20 and 70%). Even though packets were transmitted in burst, we set the inter packet interval (IPI) duration to 20 ms, so that each node has sufficient time to receive packets and to store link quality metrics locally. With the statistics we obtained, we determined offline (1) the number of distinct link quality states for each link using the K-mean clustering algorithm, (2) the link quality state transition probabilities, (3) the expected duration a link remains in the same state, and (3) the expected number of packets that can be transmitted in burst for each state. We compared our strategy with (a) a base line in which packets are transmitted in burst without taking knowledge of link quality fluctuation into account and (b) a model we proposed previously [10] and uses the conditional probability distribution function to estimate the expected stable duration of a link, where stability is defined as the link quality staying above a set threshold.

4.1 Cluster Size

As we already mentioned above, previous studies suggest that link quality can be categorised into three fixed states, namely, good (perfect), intermediate (bursty) and bad. While this is a plausible classification, it may not apply for all types of links. In our investigation, we considered different values of k and measured the packet delivery capacity of the links. Figure 5 compares our packet transmission scheme for different values of k with the baseline. The measurement was obtained by transmitting 1000 packets for each test case and for each of the links. For our scheme we considered cluster sizes of 2, 3, and 4. As can be seen from the figure, our transmission scheme improved packet delivery, regardless of

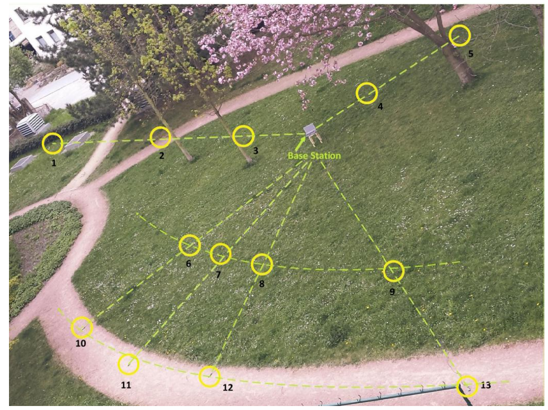

Figure 3: A wireless sensor network deployed in a garden to investigate the fluctuation of link quality over time (circles are added to highlight the position of the nodes). TelosB sensor platforms integrating CC2420 radio were used to establish the network.

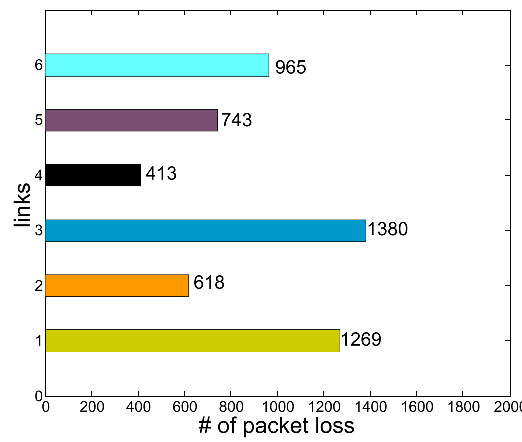

Figure 4: Number of packet lost in different links during burst transmission.

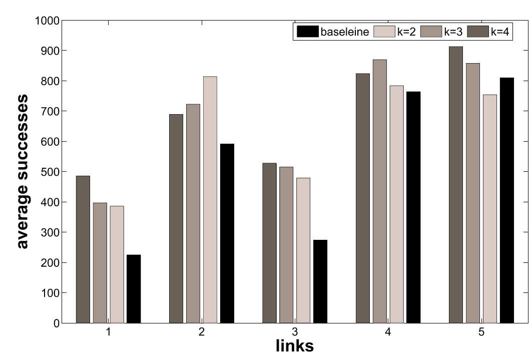

Figure 5: Comparison of the packet delivery capacity of different links with different values for k.

the value of k. Nevertheless, for link 1, 3, and 5, the value of k that resulted in the highest packet delivery was 4, whereas for link 2, it was 2, and for link 3 it was 3. This clearly indicates that the cluster size depends on the specific nature of a link.

4.2 Packet Delivery Capacity

After we determined the optimal cluster size for each link, we compared our transmission scheme with both the baseline and our previous transmission scheme. To test the reproducibility of our scheme, we varied the number of packets we transmitted in burst as follows: 500, 1000, 2000, 3000, 4000, 5000, and 10000. In the present transmission scheme, burst transmission takes place within a single state followed by a pause before a state transition takes place, which means, the maximum burst size within a state is bound by the expected duration of the state whereas in the previous scheme there is no notion of state and a burst can have any size. Figure 6 compares the performance of our transmission scheme with the baseline and with our previous scheme. For this particular case, we transmitted 1000 packets. Both schemes produced appreciable gain compared to the baseline (confirming to the importance of efficient transmission scheme at the MAC layer) but the present scheme outperformed the previous one in almost all the test cases.

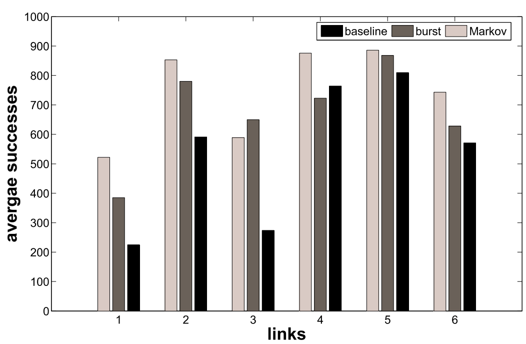

Figure 6: Comparison of the packet delivery capacity of our transmission scheme with the baseline and a previous scheme based on conditional CDFs of SNR.

5. CONCLUSION

In this paper we studied link quality fluctuation in a static deployment and proposed a two-stage Markov model to predict stable durations to schedule packet transmission in these durations only. Our approach is realised in three steps: First the link quality fluctuation is divided into countable regions using a K-mean clustering algorithm. We employed the *silhouette method* to identify the optimal number of regions that sufficiently characterise link quality fluctuation. We considered these regions as states to model link quality fluctuation as a discrete Markov process. Second, we used statistics from ARR vs. SNR relationship to determine off-line the state transition probabilities. Using state transition probabilities, we computed the expected duration a link stays in a given state. Third, for each state, we estimated the number of packets that can be transmitted in burst by applying a discrete Markov process on the binary sequence we constructed from received acknowledgement packages. We tested our approaches using an outdoor deployment consisting of on 14 TelosB nodes. The experiments results confirm that our approach improves the packet delivery capacity of wireless links. Altogether, we transmitted more than 50,000 packets to obtain sufficient statistics for our model and more than 70,000 packets to evaluate the model. Our approach improved the packet delivery capacity of the links by up to 40% when compared with the baseline approach and by up to 25% when compared with the scheme that employs conditional CDF.

6. ACKNOWLEDGMENTS

This work has been partially funded by the German Research Foundation (DFG) under project agreement: DA 1211/5-1.

7. REFERENCES

[1] M. H. Alizai, O. Landsiedel, J. Á. B. Link, S. Götz, and K. Wehrle. Bursty traffic over bursty links. In *Proceedings of the 7th International Conference on Embedded Networked Sensor Systems, SenSys 2009, Berkeley, California, USA, November 4-6, 2009*, pages 71–84, 2009.

[2] S. Duquennoy, F. Österlind, and A. Dunkels. Lossy links, low power, high throughput. In *Proceedings of the 9th ACM Conference on Embedded Networked Sensor Systems*, SenSys '11, pages 12–25, New York, NY, USA, 2011. ACM.

[3] W. Fang, Q. Zhou, Z. Wang, and Q. Liu. An adaptive transmission scheme for wireless sensor networks. *International Journal of Future Generation Communication & Networking*, 6(1), 2013.

[4] S. Liu, R. Srivastava, C. E. Koksal, and P. Sinha. Pushback: A hidden markov model based scheme for energy efficient data transmission in sensor networks. *Ad Hoc Networks*, 7(5):973 – 986, 2009.

[5] S. P. Lloyd. Least squares quantization in PCM. *IEEE Transactions on Information Theory*, 28(2):129–136, 1982.

[6] C. V. Phan, Y. Park, H. Choi, J. Cho, and J. G. Kim. An energy-efficient transmission strategy for wireless sensor networks. *Consumer Electronics, IEEE Transactions on*, 56(2):597–605, May 2010.

[7] L. R. Rabiner. A tutorial on hidden markov models and selected applications in speech recognition. In *PROCEEDINGS OF THE IEEE*, pages 257–286, 1989.

[8] P. Rousseeuw. Silhouettes: A graphical aid to the interpretation and validation of cluster analysis. *J. Comput. Appl. Math.*, 20(1):53–65, Nov. 1987.

[9] K. Srinivasan, M. A. Kazandjieva, S. Agarwal, and P. Levis. The beta-factor: measuring wireless link burstiness. In *Proceedings of the 6th International Conference on Embedded Networked Sensor Systems, SenSys 2008, Raleigh, NC, USA, November 5-7, 2008*, pages 29–42, 2008.

[10] J. Wen, Z. Ansar, and W. Dargie. A link quality estimation model for energy-efficient wireless sensor networks. In *IEEE,International Conference on Communications, ICC 2015, London, England, June 8-12, 2015*, 2015.