Fergus, P, Hussain, A, Al-Jumeily, D and Radi, N

A position paper on predicting the onset of nocturnal enuresis using advanced machine learning

A Position Paper on Predicting the Onset of Nocturnal Enuresis Using Advanced Machine Learning

Paul Fergus[1], Abir Hussain[1], and Dhiya Al-Jumeily[1], Naeem Radi[2]

[1]Liverpool John Moores University, Byrom Street, Liverpool, L3 3AF, UK.
{P.Fergus, A.Hussain, D.Aljumeily}@ljmu.ac.uk
[2]Al-Khawarizmi International College, Abu Dhabi, UAE.
n.radi@khawarizmi.com

Abstract. Bed-wetting during normal sleep in children and young people has a significant impact on the child and their parents. The condition is known as nocturnal enuresis and its underlying cause has been subject to different explanatory factors that include, neurological, urological, sleep, genetic and psychosocial influences. Several clinical and technological interventions for managing nocturnal enuresis exist that include the clinician's opinions, pharmacology interventions, and alarm systems. However, most have failed to produce any convincing results. Clinical information is often subjective and often inaccurate, the use of desmopression and tricyclic antidepressants only report between 20% and 40% success, and alarms only a 50% success fate. This position paper posits an alternative research idea concerned with the early detection of impending involuntary bladder release. The proposed framework is a measurement and prediction system that processes moisture and bladder volume data from sensors fitted into undergarments that are used by patients suffering with nocturnal enuresis. The proposed framework represents a level of sophistication in nocturnal enuresis treatment not previously considered.

Keywords: Nocturnal Enuresis, Bedwetting, Machine Learning, Classification, Neural Networks, Sensors

1. Introduction

Although urination is a function performed effortlessly by healthy humans, it is an extremely complex process that involves the rapid and precise coordination of numerous muscles and nerves in the ureter, bladder, sphincter and urethra (Porth, 2007). Nocturnal enuresis (incontinence or bedwetting) is an event that is commonly considered as a disruption to the normal process in achieving continence. Nocturnal enuresis occurs involuntary during sleep without any inherent suggestions of frequency or pathophysiology[1] and its etiology is complex. However, it is believed to be caused by three main non-exclusive pathogenic mechanisms: nocturnal polyuria (passing large amounts of urine at night and normal amounts during the day) (Fatah,

[1] http://www.nice.org.uk/

Shaker, Ismail, & Ezzat, 2009), detrusor overactivity (involuntary contractions during the filling phase) (Prieto et al., 2012), and increased arousal thresholds (a patient's inability to waken in response to signals from a full bladder) (Dhondt et al., 2009). The underlying reason for these conditions has been subject to different explanatory factors that include, neurological, urological, sleep, genetic and psychosocial influences (Butler, 2004; Campbell, Cox, & Borowitz, 2009; Culbert & Banez, 2008; Robson, 2009). Furthermore, general parental knowledge of the causes and effective treatments for Nocturnal Enuresis (NE) is lacking. Only 55% reported they would seek medical care for their child with NE and only 28% reported awareness of effective treatments (Schlomer, Rodriquez, Weiss, & Cropp, 2013).

The condition is socially disruptive and stressful and is reported to affect 20-25% of five year olds, 5% at 10 years, and 1-2% of 15 year olds (Kennea & Evans, 2000). Data from UK Avon Longitudinal Study of Parents and Children (ALSPAC) put prevalence at 20% at 10 years, 9% at nine years and 1% at 15 years (Darling, 2010). Nocturnal enuresis can have profound effects on a child, low self-esteem (Thibodeau, Metcalfe, Koop, & Moore, 2013), social isolation (de Bruyne et al., 2009), and child abuse triggered by bedwetting (Can, Topbas, Okten, & Kizil, 2004). Although, primary and secondary care interventions help, it has a major impact on the quality of life and healthcare resources. According to the British Association of Urological Surgeons (BAUS) between three and six million people in the UK suffer with urinary incontinence of which nocturnal enuresis is a subset of[2]. Urinary incontinence collectively has a significant cost implication, with conservative estimates suggesting that £424 million is spent annually on treatment in the UK

In this position paper, we focus on using sensors and artificial neural networks to determine the onset of a voiding episode before it occurs. This is achieved by utilizing sensors to detect moisture and bladder volume and a personalized alarm system that utilizes a neural network to train the system and predict the onset of voiding episodes.

2. Nocturnal Enuresis: Diagnosis and Treatment

A child that is at least five years old and experiencing bed wetting episodes at least twice a week for a minimum of three months would be diagnosed as suffering with nocturnal enuresis (Bettina, Shapira, & Dahlen, 2010). Investigations are triggered by complaints from the parents or child following presentation to a General Practitioner (GP) or referral to a specialist provider (Nalbantoglu et al., 2013a). At the initial assessment, clinicians are mindful of the risk of parent intolerance towards their child's nocturnal enuresis since this can affect the treatments offered. During the initial assessment, a general history is completed to develop an understanding of the pattern of bedwetting over the previous few weeks. Further enquiry will include questions on urgency, frequency, and the type and amount of drinks consumed. Diaries are used as a self-reporting tool to record historical information (Bradley et al., 2011). A physical examination following an initial assessment is often required

[2] http://www.baus.org.uk/

and laboratory tests requested to exclude other diseases, such as diabetes mellitus, urinary tract infection, and diabetes insipitus (Nalbantoglu et al., 2013b), (Vande Walle et al., 2012). Physical examinations include abdominal/flank examination for masses, bladder distension, and relevant surgical scars; examination of the perineum and external genitalia and neurological testing (Abrams et al., 2010) is completed.

Lifestyle management is a first-line intervention that is useful during the exploratory stages of diagnosis, however, it is reported that only 20% of patients suffering with nocturnal enuresis respond successfully, while 80% will need additional treatment (Lottmann & Alova, 2007). One approach is to use alarms, which have produced mixed results that range between 50% and 80% depending on the population (children and families need to be highly motivated) (Glazener & Evans, 2007). In another approach pharmacology interventions have also been routinely used in the treatment of nocturnal enuresis. The use of desmopressin shows that one third of children remain dry; one third there is a partial effect, and in the remaining third it has no effect at all (Glazener & Evans, 2002).

There have been several technological interventions for managing nocturnal enuresis that focus on detection and more recently on prediction, which have largely produced disappointing results. Arguably the earliest recorded attempt is the work of (Butler, 1994) who used a urine alarm system to alert the clinical staff at a hospital when bedwetting episodes by patients occurred (the problem is that the event has already happened and requires sheets and cloths to be washed and changed). Nilsson et al. (Nilsson & Gulliksson, 2011) proposed a similar alarm system that uses a moisture sensing mechanism fitted into undergarments that alert patients and careers when fixed levels of moisture are detected (again the event has already happened).

3. Predicting the Onset of Nocturnal Enuresis (PRONE)

The discussion so far has highlighted a number of ways to treat nocturnal enuresis. Some of these include medication, alarms and the use of advanced sensor technology. Whilst these do benefit children and their careers, they do not stop the occurrence of bedwetting and in many instances, only alert the child or parent once the event has already occurred. This means that the child has to deal with the effects of bedwetting, which include, changing cloths and bedding, embarrassment and shame and the stigma this brings. This position paper describes a solution for a possible framework to treat nocturnal enuresis that goes far beyond any existing solutions to date.

3.1 Sensor Platform

The proposed system, illustrated in Figure 2, provides an overview of the logical architecture that comprises the framework. The system operates in two modes; training mode and prediction mode.

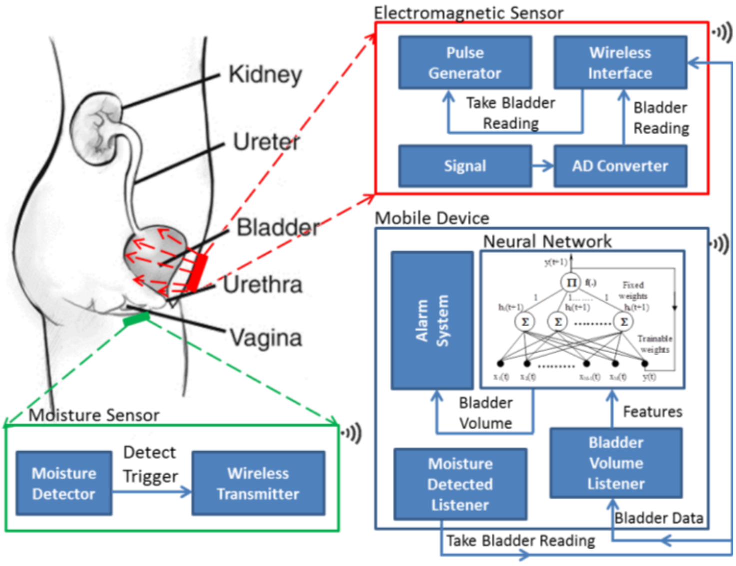


Figure 1: Proposed Prediction Framework of Nocturnal Enuresis

In the training mode, the system monitors the voiding habits of children during normal sleep. The training phase monitors the initial occurrence of moisture in the undergarment. This triggers a pulse generator in the electromagnetic sensor (also fitted into the undergarment above the navel), to start sending electromagnetic waves to decipher how full the bladder is. These values are wirelessly transmitted to the mobile device and in turn passed to the neural network to predict the volume of urine in the bladder. This value is used to configure an alarm that is specific to the patients voiding habits. The learning phase is configurable, but it is envisaged that several weeks of data will be required to provide an estimate of the bladder volume and voiding events. Following the completion of this training phase, an alarm will be configured to a percentage below the averaged bladder volume and voiding episodes learned by the system of the training period.

During prediction mode, electromagnetic data is continuously (or at set intermittent times), streamed wireless to the mobile device. This data is passed to the neural network and the predicted bladder volume level is passed to the alarm system. If the value is equal to or greater than the pre-configured alarm threshold as determined during the training phase, an alarm will be triggered that prompts the child to wake up and go to the toilet. The principle goal is to wake then just before the onset of a voiding episode.

3.2 Electromagnetic Wave Sensors

The communication platform is a Bluetooth low energy (BLE) network with supporting services for data processing, aggregation, storage and distribution. All sensors have a BLE interface connecting them to the network. Sensors transmit data using the Generic Attribute Profile (GATT) protocol in BLE (Gupta, 2013) and all data is pre-processed using signal processing techniques. In the first instance, data is used to set the parameters of the algorithm and during runtime data is used for real-time prediction. The sensors are robust to variations in skin, fat, muscle thickness and bladder sizes. Electromagnetic waves are attenuated while passing through the bladder. Different attenuation is encountered at different frequencies. This is primarily because different body tissue, such as muscle, fat and skin own different relative permittivity. This means that electromagnetic waves undergo numerous reflections from the boundary between two tissues/organs that have different relative permittivity. This method is proposed to detect the presence of water because the value of the relative permittivity of the water (in this instance urine) is much larger than the values of the relative permittivity of the surrounding organs and tissues.

A large reflection of the incident electromagnetic signal pulse occurs. The position, amount of water, and the water concentration in the reflecting organ, can be estimated since the electromagnetic signals own a fine range resolution and good penetration ability. The signals from the transmitting and receiving antenna are processed using classification and prediction algorithms, which represent the relation between the signal frequencies and bladder volume. Bladder volume prediction is triggered during training by moisture sensors fitted into undergarments that consist of two electricity conductors separated by an insulated moisture absorbing material. Figure 2 illustrates the two sensor systems

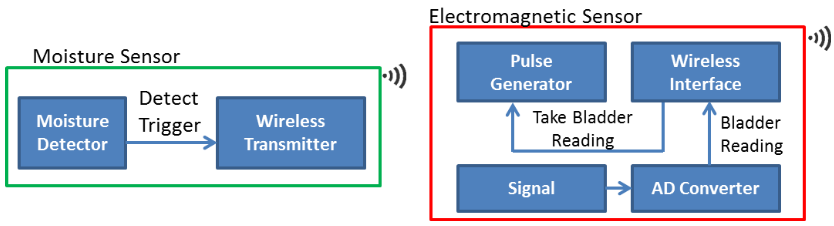


Figure 2: Moisture and Bladder Volume Sensor

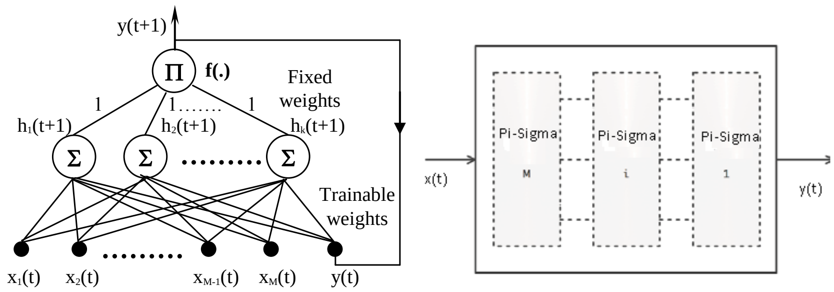
In prediction mode, a similar process is followed. Data is streamed or sampled at set time intervals, as discussed above, vectors are created and transmitted for signal processing and bladder volume prediction.

3.3 Adaptive Neural Network Architecture

A system to predict the occurrence of nocturnal enuresis before it occurs is provided by the proposed framework. The purpose of the system is to raise an alarm to the user using a mobile device based on the information collected from the developed sensor technology. Since the bladder volume varies from one person to the other, an adaptive system will be designed to personalize prediction and alarm thresholds. A pipelined structure similar to the adaptive fully recurrent pipelined neural network architecture proposed by Haykin and Li (Haykin, 1995) for the prediction of future occurrences of bedwetting, is introduced. The main structure of the proposed network is the recurrent pi-sigma unit (Shin & Ghosh, 1991) as shown in

Figure 3 (a), due to their simplicity and the high learning capabilities of higher order neural networks, which make them suitable for mobile device processing.

The network comprises a number of concatenated recurrent pi-sigma neural networks. It is designed to adaptively predict highly nonlinear and non-stationary signals, such as the bedwetting signal. Similar to the adaptive fully recurrent pipelined neural network architecture, the proposed network is designed using the principles of divide and conquer. This means that to solve a complex problem, it has to be broken into a number of smaller sub-problems. The proposed network is called pipelined recurrent pi-sigma neural network (PRPSN). Figure 3 (b) shows the general structure of the proposed network, while Figure 4 shows a specific structure of the proposed network with two modules for the recurrent pi-sigma units and m external inputs.



a) Structure of recurrent Pi-sigma Network

b) Proposed Pipelined Pi-sigma Network

Figure 3: (a) The structure of the Recurrent Pi-sigma network (b) The proposed pipelined Pi-sigma network

Let q represent the total number of recurrent pi-sigma neural networks, which are concatenated with each other. Each recurrent pi-sigma neural network is called a unit (or a module) and consists of M-1 external inputs, except for the last unit, which consists of M external inputs. All the units of the PRPSN receive the output from previous units as input, except the last module in the proposed pipeline.

In Figure 4, the inputs and outputs, as well as, the processing equations of the pipelined recurrent pi-sigma neural network are presented.

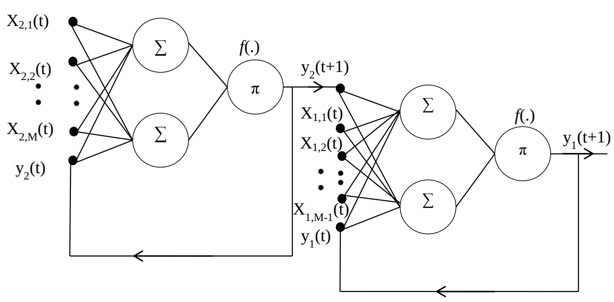


Figure 4: Module recurrent pi-sigma pipelined neural network architecture with *m* external inputs and second order pi-sigma units.

If *S(t)* represents the nonlinear and non-stationary signal at time *t* obtained from the sensor, then the external input vector presented to the i^{th} module of the pipelined pi-sigma network is defined as follows:

$$X_i(t) = [S(t-i)\,\mathrm{S(t - (i+1)), \ldots\ldots, S(t - (i+M-2))}]^T \text{ , for } \mathrm{i} \neq \mathrm{q}$$

$$X_i(t) = [S(t)\,\mathrm{S(t - i), S(t - (i+1) \ldots\ldots, S(t - (i+M-1))}]^T \text{ , for i=q}$$

(1)

Let y_i represent the output of module *i*, which is defined as follows:

$$y_i(t) = f(v_i(t))$$

(2)

where *f* is a nonlinear transfer function and v_i is the net internal activation of module *i*.

For the last module of the polynomial pipelined network:

$$v_q(t) = \prod_{L=1}^{k} h_{q,L}(t+1)$$

$$\mathrm{h}_{\mathrm{a,L}}(t+1) = \sum_{m=1}^{M} w_{q,Lm} \cdot s_{q,m}(t) + w_{q,L(M+1)} \cdot y_q(t-1)$$

(3)

where *k* is the order of the recurrent pi-sigma unit.

For all other modules:

$$v_i(t) = \prod_{L=1}^{k} h_{i,L}(t+1)$$

$$\mathrm{h}_{\mathrm{i,L}}(t+1) = \sum_{m=1}^{M-1} w_{i,Lm} \cdot s_{i,m}(t) + w_{i,L(M+1)} \cdot y_i(t-1) + w_{i,L(M+2)} \cdot y_{i+1}(t)$$

(4)

The proposed network can be trained using the real-time learning algorithm developed by Williams and Zipser [62]. Instead of assuming that the weights are constants during the whole trajectory, this condition is relaxed and the weights are updated for each input pattern presentation. The advantage of this learning algorithm is that the epoch boundaries are no longer required, making the implementation of the algorithm simpler and letting the network be trained for an indefinite period.

The learning algorithm starts by initializing the weights of one of the network units to small random values. Then, the weights of this unit are trained and used as the initial weights for the PRPSN. The PRPSN is trained adaptively in which the errors produced from each module are calculated and the overall cost function of the PPNN is defined as follows:

$$\varepsilon(\mathrm{t}) = \sum_{\mathrm{i}=1}^{\mathrm{q}} \lambda^{\mathrm{i}-1} \mathrm{e}_{\mathrm{i}}^{2}(\mathrm{t}) \tag{5}$$

where λ is an exponential forgetting factor selected in the range (0, 1). At each time t, the output of each module $y_i(t)$ is determined and the error $e_i(t)$ is calculated as the difference between the actual value expected from each unit i and the predicted value $y_i(t)$. The weights are iteratively updated by gradient descent:

$$\Delta w_{ml}(t) = -\eta \frac{\partial \varepsilon(t)}{\partial w_{ml}} \tag{6}$$

where □ is the manually adjusted gain and

$$\begin{aligned} \frac{\partial \varepsilon(t)}{\partial w_{ml}} &= 2\sum_{i=1}^{q} \lambda^{i-1} e_i(t) \frac{\partial e_i(t)}{\partial w_{ml}}, \\ &= -2\sum_{i=1}^{q} \lambda^{i-1} e_i(t) \frac{\partial y_i(t)}{\partial w_{ml}} \end{aligned} \tag{7}$$

Define

$$p_{ml}^{i}(t) = \frac{\partial y_i(t)}{\partial w_{ml}} \tag{8}$$

Then, the values of the triple $p_{ml}^{i}(t)$ matrix are updated by differentiating the processing equations as follows:

$$P_{ml}^{i}(t) = f'\left(\prod_{L=1}^{k} h_L\right) \prod_{\substack{L=1 \\ L \neq m}}^{k} h_L \left(Z_l(t) + w_{m(M+2)} P_{ml}^{i}(t-1)\right) \tag{9}$$

Where

$$z_l(t) = \begin{cases} S(t-(l+L-1)), & 1 \le \mathrm{L} \le \mathrm{M}, \\ \mathrm{y}l(t) & \mathrm{L} = \mathrm{M}+1, \end{cases} \quad \text{for i = q}$$

$$z_l(t) = \begin{cases} y_{1\text{-}1}(t) & L = 1 \\ S(t-(l+L-1)), & 1 < L \leq M\text{-}1, \quad \text{for } i \neq q \\ y_1(t) & L = M+1, \end{cases}$$

(10)

The proposed neural network architecture will be used to capture the properties of the sensor signals and its structure will be adapted according to the training period. The values will be predicted adaptively over time.

3.4 Mobile Platform

In the network configuration, a mobile device will act as the GATT server. All data will be pre-processed using signal processing techniques. Features are extracted from the data and passed to the neural network to predict the bladder volume level. This process is performed in both training and prediction mode – in training mode it is used to set the alarm thresholds in relation to the detection of moisture and the volume level in the bladder. In prediction mode it is used to determine whether an alarm threshold has been reached – if this is the case an alarm is raised to wake the child as shown in Figure 5.

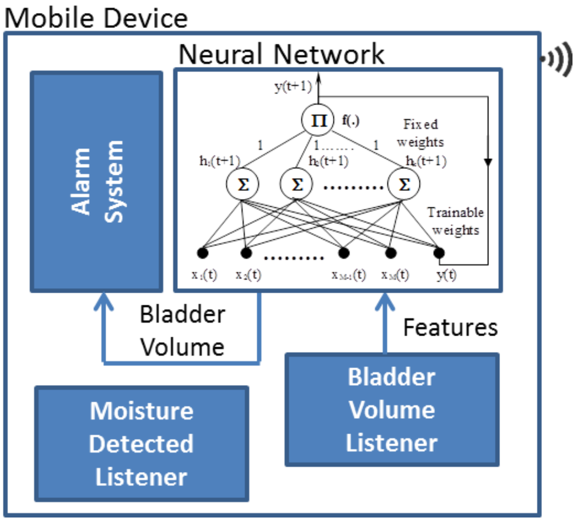


Figure 5: Mobile Platform

The proposed framework goes far beyond previous attempts to predict the likely time a child will wet the bed. It offers the means for the automated extraction of bladder measurements, by using advanced computer algorithms never attempted before in the prediction of nocturnal enuresis events that occur prior to bed-wetting. Overall, it is an adventurous medium risk/very-high impact appraoch, which will attempt to solve a significant real-world problem with advanced computer science methodologies.

4. Discussion

The timeliness of this work can be realistically judged in the context of large number of patients and the demographics of the population. The overall worldwide prevalence of unary incontinence is said to be 200 million people. In the UK, the figure is between three and six million and in the US, it is said to be 25 million. The economic cost of treating adults over the age of 40 suffering with urinary incontinence annually was estimated to be £536 million in 1999/2000 prices. In addition, it is estimated to cost the individual £207 million for managing their symptoms (£29 million and £178 million for men and women, respectively). The conservative estimate for treating children and adolescents is £424 million annually in the UK. In 2005, the annual cost-of-illness estimates for urinary incontinence in Canada, Germany, Italy, Spain, Sweden, and the United Kingdom was 7 billion euros. A US cost-of-illness study reported a total cost of $66 billion in 2007. These figures are likely to rise significantly over the next 20 years as awareness of the condition and the mean age of the population increases (Milsom et al., 2013).

There is no real “gold standard” for the diagnosis and treatment of nocturnal enuresis. Taking into account the important role of prediction in the clinical assessment of NHS patients, and the large volume of nocturnal enuresis research articles based on alarm systems, we believe that there will be significant interest in the framework posited in this paper as it represents a level of sophistication and accuracy in nocturnal enuresis treatment not previously considered.

5. Conclusion

This paper has proposed a novel, low cost measurement and prediction system that detects the onset of nocturnal enuresis episodes before they occur, which current technologies cannot do. Commercial scale PrONE has the capacity to revolutionize the treatment of nocturnal enuresis and other incontinence conditions, while offering an affordable personalized device that allows children and their parents to manage their condition in the home. In the UK alone, PrONE presents the NHS with a real opportunity to treat nocturnal enuresis under the recommendations set out by NICE, and will also help the NHS significantly reduce the costs associated with treating this condition.

The potential market for PrONE is vast, as personalized prediction systems can be used to offset the need for diagnostic and healthcare services. PrONE will improve the overall success rate of treatments (14 consecutive dry nights) while reducing relapses and help to gain a better and standardized understanding of the condition. It will reduce NHS costs and also costs incurred by parents (cleaning costs, mattress replacement, disposable products required). The anticipated efficiency of PrONE is such that it will standardize diagnosis and treatment compared with existing solutions and procedures as a result of its ease of use, data collection and communication capabilities between the child, parent and care practitioners.

There is no other product on the market that covers such technology that can help to treat and understand nocturnal enuresis personalized to an individual's condition and generalizable across all suffers of nocturnal enuresis.

References

Abrams, P., Andersson, K. E., Birder, L., Brubaker, L., Cardozo, L., & Al., E. (2010). Forth International Consultation on Incontinence Recommendations of the International Scientific Committee: Evaluation and Treatment of Urinary Incontinence, Pelvic Organ Prolapse and Fecal Incontinence. *Neurourology and Urodynamics*, *29*(1), 213–40.

Bettina, E., Shapira, E., & Dahlen, P. (2010). Therapeutic Treatment Protocol for Enuressi Using and Enuresis Alarm. *Journal of Counseling & Development*, *88*(2), 246–252.

Bradley, C. S., Brown, J. S., van Den Eeden, S. K., Schembri, M., Ragins, A., & Thom, D. H. (2011). Urinary incontinence self-report questions: reproducability and agreement with bladder diary. *International Journal on Urogynedol*, *22*(12), 1565–71.

Butler, R. J. (1994). *Nocturnal Enuresis. The child's experience* (p. 192).

Butler, R. J. (2004). Childhood nocturnal enuresis: Developing a conceptual framework. *Clinical Psychology Review*, *24*(8), 909–31.

Campbell, L. K., Cox, D. L., & Borowitz, S. M. (2009). Elimination Disorders. In *Handbook of Pediatric Psychology* (p. 808).

Can, G., Topbas, M., Okten, A., & Kizil, M. (2004). Child abuse as a result of enuresis. *Pediatrics International*, *46*(1), 64–66.

Culbert, T. P., & Banez, G. A. (2008). Wetting the bed: Integrative approaches to nocturnal enuresis. *Explore*, *4*(3), 215–220.

Darling, J. C. (2010). Management of Nocturnal Enuresis. *Trends in Urology, Gynaecology and Sexual Health*, *15*(3), 18–22.

De Bruyne, E., van Hoecke, E., van Gompel, K., Verbeken, S., Hoebeke, P., & Vande Walle, J. (2009). Problem Behaviour, Parental Stress and Enuresis. *The Journal of Urology*, *182*(4), 2015–2021.

Dhondt, K., Raes, A., Hoebeke, P., van Laecke, E., van Herzeele, C., & Vande Walle, J. (2009). Abnormal Sleep Architecture and Refractory Nocturnal Enuresis. *Journal of Urology*, *182*(4), 1961–1965.

Fatah, D. A., Shaker, H., Ismail, M., & Ezzat, M. (2009). Nocturia Polyuria and Nocturnal Arginine Vasopression (AVP): A Key Factor in the Pathophysiology of Monosymptomatic Nocturnal Enuresis. *Neurourology and Urodynamics*, *28*(6), 506–509.

Glazener, C. M., & Evans, J. H. (2007). Alarm Interventions for Nocturnal Enuresis in Children (Cochrane Review). *The Cochrane Library*.

Glazener, C. M., & Evans, J. M. (2002). Desmopressin for Nocturnal Enuresis. *Cochrane Database Systematic Review*, *CD002112*.

Gupta, N. (2013). *Inside Bluetooth Low Energy*. *IEEE Transactions on Instrumentation and Measurement* (p. 210).

Haykin, L. (1995). Nonlinear adaptive prediction of nonstationary signals. *IEEE Transactions of Signal Processing*, *43*(2), 526–535.

Kennea, N., & Evans, J. (2000). Drug treatment of nocturnal enuresis. *Paediatric and Perinatal Drug Therapy*, *4*(1), 12–18.

Lottmann, H. B., & Alova, I. (2007). Primary Monosymptomatic Nocturnal Enuresis in Children and Adolescents. *The International Journal of Clinical Practice*, *61*(s155), 8–16.

Milsom, I., Coyne, K. S., Nicholson, S., Kvasz, M., Chen, C., & Wein, A. J. (2013). Global Prevalence and Economic Burden of Urgency Urinary Incontinence: A Systematic Review. *European Urology*, *In Press*.

Nalbantoglu, B., Yazici, C. M., Nalbantoglu, A., Guzel, S., Topcu, B., Guzel, E. C., … Mintas, N. E. (2013a). Copeptin as a Novel Biomarker in Nocturnal Enuresis. *Pediatric Urology*, *In Press*.

Nalbantoglu, B., Yazici, C. M., Nalbantoglu, A., Guzel, S., Topcu, B., Guzel, E. C., … Mintas, N. E. (2013b). Copeptin as a Novel Biomarker in Nocturnal Enuresis. *Pediatric Urology*, *In Press*.

Nilsson, H., & Gulliksson, J. (2011). An Incontinence Alarm Solution Utilizing RFID-based Sensor Technology. In *IEEE International Conference on RFID-Technologies and Applications* (pp. 359–363).

Porth, C. M. (2007). *Essentials of Pathophysiology: Concepts of Altered Health States* (p. 1149).

Prieto, L., Castro, D., Esteban, M., Salinas, J., Jimenez, M., & Mora, A. (2012). Descriptive Epidemiological Study of the Diagnosis of Detrusor Overactivity in Urodynamic Units in Spain. *Actas Urologicas Espanolas*, *36*(1), 21–28.

Robson, W. L. M. (2009). Evaluation and management of Enuresis. *New England Journal of Medicine*, *360*(14), 1429–1436.

Schlomer, B., Rodriquez, E., Weiss, D., & Cropp, H. (2013). Parental beliefs about nocturnal enuresis causes, treatments, and the need to seek professional medical care. *Journal of Pediatric Urology*, *In Press*.

Shin, Y., & Ghosh, J. (1991). The pi-sigma network: An efficient higher-order neural network for pattern classification and function approximation. In *IEEE International Conference on Neural Computing* (pp. 13–18).

Thibodeau, B. A., Metcalfe, P., Koop, P., & Moore, K. (2013). Urinary Incontinence and quality of life in children. *Pediatric Urology*, *9*(1), 78–83.

Vande Walle, J., Rittig, S., Bauer, S., Eggert, P., Marshall-Kehrel, D., & Tekgul, S. (2012). Practical Consensus Guidelines for the Management of Enuresis. *European Journal of Pediatrics*, *171*(6), 971–983.