CLAIMS

1. A passive RFID health monitoring device, comprising:

an antenna for receiving a continuous interrogation signal;

a passive RFID chip coupled to the antenna comprising:

a power harvester circuit coupled to the antenna that obtains power from the interrogation signal and converts it to direct current (DC) to provide operating power for at least one other circuit in the passive RFID chip;

a health data amplifier circuit coupled to the power harvester circuit and having at least one port for receiving a cyclical health data signal from at least one sensor, the health data amplifier circuit operative to receive operating power from the power harvester circuit and use the power to amplify the received cyclical health data signal;

a data detector circuit coupled to the health data amplifier circuit that receives the amplified cyclical health data signal and detects the occurrence of at least one event of interest in each cycle of the cyclical health data signal, and outputs a signal containing information of each detected event of interest; and

a passive RFID tag coupled to an antenna and operative to output via the antenna a default continuous backscatter signal responsive to the received interrogation signal, the RFID tag coupled to the data detector circuit to receive the signal containing information of each detected event of interest, and further operative to modify the backscatter signal to include at least a portion of the information of each detected event of interest.

2. The device of claim 1, wherein the cyclical health data signal includes at least one electrocardiographic (ECG) signal from at least one ECG sensor operationally coupled to a subject, the ECG signal containing information of the condition of the subject's heart.

3. The device of claim 2, wherein:

the event of interest is the occurrence of the peak of a QRS Complex (R) in each cycle of the ECG signal;

the data detector is a heart rate detector that detects the peak of the R event in each cycle, the heart rate detector configured to output a pulsed binary waveform that switches from a first value to a second value when it detects the peak of the R event, remains at the second value for a predetermined duration, and returns to the first state at the end of the predetermined duration.

4. The device of claim 3, wherein the RFID tag does not output the continuous backscatter signal when the pulsed binary waveform has the second value, and does output the backscatter signal when the pulsed binary waveform has the first value.

5. The device of claim 3, wherein the cyclical health data signal includes a respiration signal that arises in at least one respiration sensor responsive to a cyclical motion caused by a subject's breathing, wherein:

the health data amplifier circuit has at least one port for receiving the respiration signal from the at least one respiration sensor and amplifies the respiration signal;

the data detector circuit is a respiration detector that receives the amplified respiration signal and detects the occurrence of at least one event of interest in each cycle of the respiration signal, and outputs a waveform containing information of the subject's respiration corresponding to the detected event of interest; and

the passive RFID tag is coupled to the respiration detector to receive the waveform containing the information of the subject's respiration, and is operative to modify the backscatter signal to include at least a portion of the information of the subject's respiration.

6. A passive RFID health monitor system, comprising:

the passive RFID health monitoring device of claim 1;

an RFID reader inductively coupled to the passive RFID health monitoring device, and containing a data processor operative to obtain and perform operations on the health information included in the modified backscatter signal from the RFID tag of the RFID health monitoring device.

7. The system of claim 6, wherein the operations performed on the obtained health information include calculating a rate of occurrences per minute of the cyclical health data signal sensed by the at least one sensor.

8. The system of claim 7, wherein the rate is one of a heart rate and a respiration rate.

9. A method of monitoring the health of a subject, comprising:

training a model for use in accurately characterizing new data points in a new window of time using data points corresponding to sensed information of a cyclical health data signal from a most recently completed window of time; and

detecting occurrences of an event of interest in each cycle of the cyclical health data signal using the model.

10. The method of claim 9, wherein the model training includes logistic regression and parameter extraction using the data points.

11. The method of claim 10, wherein the logistic regression and parameter extraction comprise steps including:

calculating an estimated probability that an occurrence of the event of interest is indicated by each of the data points, including estimating a parameter for use in the calculation;

estimating an error in the estimated parameter used in the probability calculation, including calculating an error in predicting an occurrence of the event of interest, and calculating an error in predicting the lack of an occurrence of the event of interest;

calculating an improved parameter for use in recalculating the probability estimate;

repeating the steps of calculating a probability estimate using a parameter, estimating an error in the parameter, and calculating an improved parameter until the value of the parameter converges; and using the converged parameter as the parameter for the model to characterize new data points.

12. The method of claim 11, wherein the estimating the probability that an occurrence of the event of interest is indicated by each of the data points includes using the data points in a calculation given by the equation:

$$h_\theta(x_i) = \frac{1}{1 + e^{-\theta x_i}}$$

where "$h_\theta (x_i)$" is the probability that a data point represents an occurrence of the event of interest or not, "x_i" represents a training data feature with index "i", and "θ" represents parameters of the model.

13. The method of claim 12, wherein the error in estimating a parameter for use in improving the estimated probability of the occurrence of the event of interest is calculated using the equation:

$$E(\theta) = \frac{-1}{m}\sum_{i=1}^{m}\{y^i \log\left(h_\theta(x_i)\right) + (1 - y^i)\log\left(1 - h_\theta(x_i)\right)\}$$

where "m" is the number of training samples with index "i", and "y" is the actual state of the output.

14. The method of claim 13, wherein after the error due to the choice of θ is determined, a new estimate of θ may be calculated using the equation:

$$\theta_{new} = \theta - \alpha\frac{\partial E(\theta)}{\partial \theta}$$

where "a" is a scaling factor that adjusts the step sizes for new values of θ.

15. A tangible data storage device on which is stored computer instructions which, when executed on a passive RFID health monitor reader, cause the reader to perform a method comprising:

training a model for use in accurately characterizing new data points in a new window of time using data points corresponding to sensed information of a cyclical health data signal from a most recently completed window of time; and

detecting occurrences of an event of interest in each cycle of the cyclical health data signal using the model.

16. The storage device of claim 15, wherein the model training includes logistic regression and parameter extraction using the data points.

17. The storage device of claim 16, wherein the logistic regression and parameter extraction comprise steps including:

calculating an estimated probability that an occurrence of the event of interest is indicated by each of the data points, including estimating a parameter for use in the calculation;

estimating an error in the estimated parameter used in the probability calculation, including calculating an error in predicting an occurrence of the event of interest, and calculating an error in predicting the lack of an occurrence of the event of interest;

calculating an improved parameter for use in recalculating the probability estimate;

repeating the steps of calculating a probability estimate using a parameter, estimating an error in the parameter, and calculating an improved parameter until the value of the parameter converges; and

using the converged parameter as the parameter for the model to characterize new data points.

18. The storage device of claim 17, wherein the estimating the probability that an occurrence of the event of interest is indicated by each of the data points includes using the data points in a calculation given by the equation:

$$h_\theta(x_i) = \frac{1}{1 + e^{-\theta x_i}}$$

where "$h_\theta (x_i)$" is the probability that a data point represents an occurrence of the event of interest or not, "x_i" represents a training data feature with index "i", and "θ" represents parameters of the model.

19. The storage device of claim 18, wherein the error in estimating a parameter for use in improving the estimated probability of the occurrence of the event of interest is calculated using the equation:

$$E(\theta) = \frac{-1}{m}\sum_{i=1}^{m}\{y^i \log(h_\theta(x_i)) + (1-y^i)\log(1-h_\theta(x_i))\}$$

where "m" is the number of training samples with index "i", and "y" is the actual state of the output.

20. The storage device of claim 19, wherein after the error due to the choice of θ is determined, a new estimate of θ may be calculated using the equation:

$$\theta_{new} = \theta - \alpha\frac{\partial E(\theta)}{\partial\theta}$$

where "a" is a scaling factor that adjusts the step sizes for new values of θ.