



Intelligent surface heating using LSTM networks

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ABSTRACT

Electrically heated blankets have been around the market for a long time. They are extremely handy during winters, as they can be used to warm beds. There have been many advances in the control systems to ensure that the desired temperature of the blanket is maintained. The drawback of such systems is its power consumption. Commercially available heating blankets use about 200 watts of power. On average, an adult's body occupies only about 60 to 70 percent of the total sleeping area of a bed. Existing technologies heat the full blanket irrespective of the users sleeping position and orientation. This results in wastage of power due to inefficient heating of the blanket. In this paper, we present an intelligent heating system that uses Long Short Term Memory (LSTM) to learn the sleeping patterns of the user to predict the future position and orientation of the user to maximize its overall efficiency.

Keywords— Long Short-Term Memory (LSTM), Intelligent Devices, Machine Learning, Automatic heat regulation, Fuzzy PD control

1. INTRODUCTION

Similar to images, beds and any other surface can also be represented as an $m \times n$ matrix. Each cell of the matrix on the surface consists of heating and force sensing cells. If the force sensor picks up a signal greater than the threshold amount, it gets activated. The first λ number of activated cells are considered for the position of the user. The value λ can be changed to achieve higher accuracy. For every time step, the sleeping position data is collected this way and fed into the Long Short Term Memory (LSTM) model. LSTM is a sequence model that can predict and sequence information such as text and audio with high accuracy. Long Short-Term Memory (LSTM) networks are a type of Recurrent Neural Network (RNN) capable of learning order dependence in sequence prediction problems. Figure 1 shows the general architecture of an LSTM model.

Here, X means information scaling, $+$ represents information addition, σ represents the sigmoid activation function, \tanh represents the \tanh activation function, $C(t-1)$ is the memory from last LSTM unit, $h(t-1)$ is the output of last LSTM unit, $C(t)$ is the new updated memory, $h(t)$ is the current output and $X(t)$ is the current input.

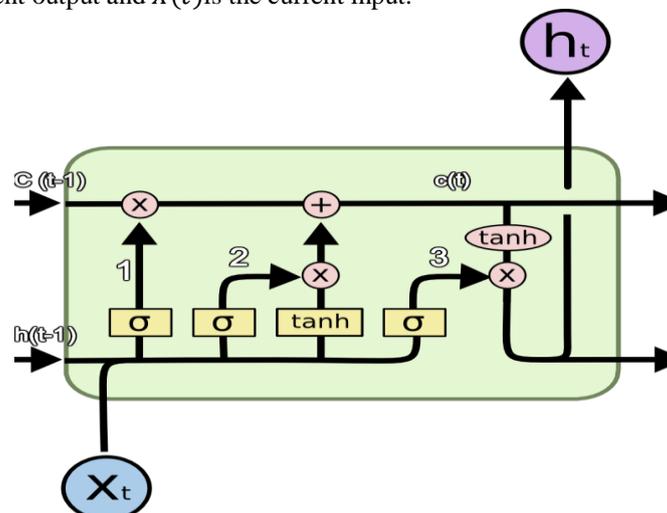


Fig. 1: LSTM Architecture

The algorithm once trained is then used to predict the next sleeping position and orientation of the person and will start heating these regions to a certain degree. When the person changes their position and orientation, those areas of the bed are reinforced with more heat, until the desired temperature of those cells is reached. In case the prediction is wrong, the heating of the predicted region is stopped, and the dataset is updated and retrained for better performances. In this way, when the user changes their sleeping positions, the bed is preheated to a certain degree to prevent discomfort, while still increasing the overall efficiency of the system.

2. METHODOLOGY

The power consumption of traditional heating blankets was measured. The heating elements and force sensing elements were fixed under the top layer of the bed. Keras and scikit-learn Python libraries were used to implement Long Short Term Memory (LSTM). The future predicted regions of the user are then heated to 50% of the actual temperature setpoint. When the user changes their position, if the prediction is right, the temperature of those regions is made to reach the desired temperature setpoint. Otherwise, the dataset is updated and retrained. Otherwise, the regions where a significant force is experienced are maintained at the desired temperature setpoint.

To ensure that such a device is safe to use and is free from temperature overshoot or undershoot, an adaptive fuzzy PD controller is employed. This control strategy ensures optimal control of the heating elements with minimum overshoot and oscillations. Figure 2 compares the response of a traditional PD controller and that of a Fuzzy PD controller.

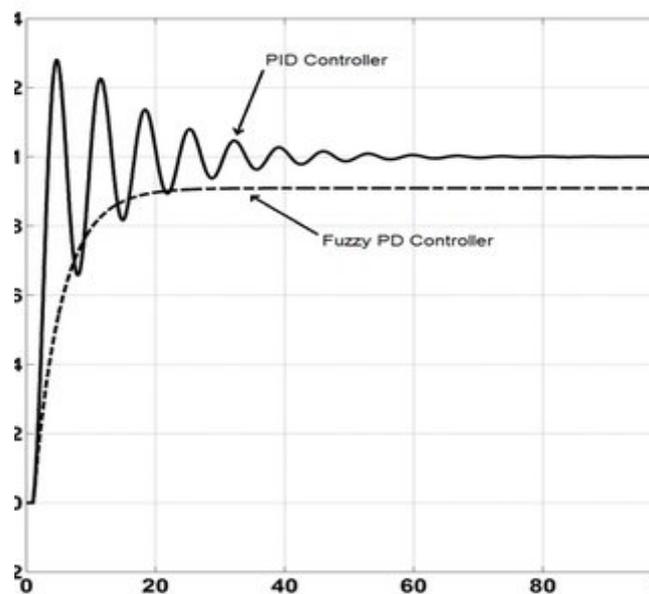


Fig. 2: Arrangement of lasers and LDR's

3. RESULTS AND DISCUSSION

The efficiency of the system was investigated under different position and orientation conditions. The overall efficiency of the conventional blankets was found to be about $55\% \pm 5\%$ whereas the efficiency of the Machine Learning assisted system was $87\% \pm 5\%$. The power loss/wastage drops from 45% to 13% creating a 32% increase in the overall efficiency of the system. The graph below shows the activated cells on the surface. The cells in blue show the current position of the user. The cells in green show the estimated/predicted next position the user could occupy. The cells in red show the actual future position of the user.

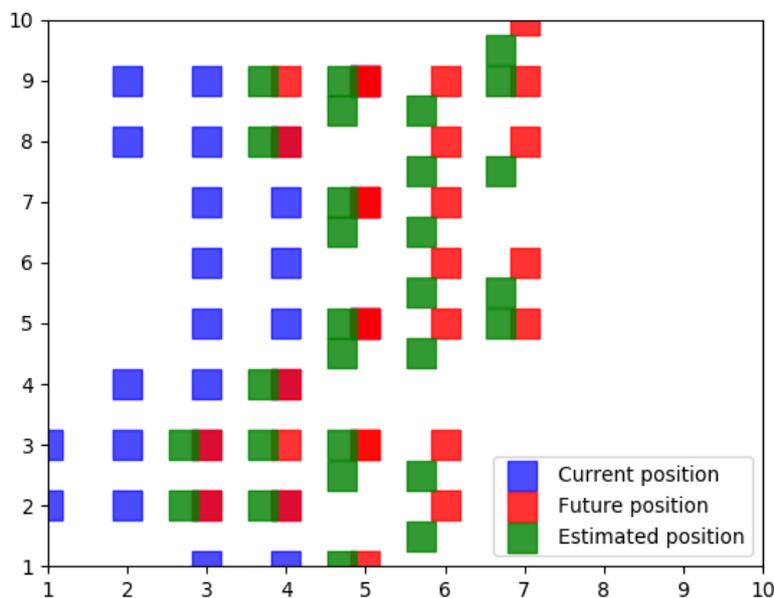


Fig. 3: Current vs Future vs. Estimated Position

4. CONCLUSION

In summary, this device was tested and analyzed using all the algorithms and methods discussed above. There is a significant improvement in the overall efficiency of the system. It meets all the design criteria for electrically heated devices and is extremely safe for daily usage.

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