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Research Article

Interpretation of Multi Sensor Measurement Results using Fuzzy Membership Function for Landslide Early Warning System

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Abstract: Central Java has several areas prone to landslides. One of them is in Tembalang district in Semarang City, Central Java Province, Indonesia. Landslides can be caused by very high rainfall and there are no trees to support the soil, resulting in land shifting. Landslide disasters are very dangerous because they cause many casualties. Therefore, an early warning system for landslides is needed. The landslide early warning system uses several sensors, namely rainfall sensors, soil moisture sensors, and soil movement. Sensors will be processed using fuzzy logic so that the results can be more accurate. Early warning of landslides has several conditions, namely, low risk to very high risk. Based on the results of real-time data collection in the landslide disaster early warning system, the results obtained were that the sensors worked well and the communication sending data to the website was working well. Data processing has been carried out and can be processed via a controller with a fuzzy logic algorithm. The results obtained were that, based on the sensor data, the early warning of landslides still had a low risk with a value of 0.5375 and a medium risk with a value of 0.5875. This is due to moderate rainfall and high soil moisture, as well as soil movement ≥ 0.1.

Keywords: early warning system, fuzzy, landslides

1 Introduction

Indonesia is a country that is prone to natural disasters. This is due to geographical position, extreme weather, and topography [1]. Indonesia's hilly and mountainous topography and many small islands make this country more vulnerable to landslides and floods [2]. High rainfall and other extreme weather phenomena such as hurricanes or tropical cyclones can cause flash floods, landslides and other damage [3, 4]. According to data from the National Disaster Management Agency (BNPB) from 2007 to 2021, there were more than 6,500 flood events that hit various regions in Indonesia. BNPB also noted that between 2007 and 2021, there were more than 11,000 landslide incidents throughout Indonesia. These landslides are spread across various regions, with West Java, Central Java, West Sumatra and South Sulawesi being the areas most frequently affected [5–7].

Central Java has several areas prone to landslides. One of them is in Tembalang district in Semarang City, Central Java Province. On Tuesday, January 2nd 2024, around 22.30 WIB, a landslide occurred in Bulusan Village, Tembalang District, which was caused by heavy rain. The chronology of the incident started with heavy rain throughout the day that caused a landslide on the talud with a length of approximately 10 meters and a width of 1 meter with a height of 1.5 meters [8].

Early warning is very important in mitigating landslides. With effective early warning, it can provide enough time for the community and the authorities to take appropriate preventive and evacuation steps [9, 10]. Several things that need to be considered regarding early warning for landslide disaster mitigation are that a monitoring system using sensors such as rainfall, soil moisture, and soil movement sensors is used to detect potential landslides more quickly [11, 12]. The data from these sensors are then processed to provide accurate and timely warnings to affected communities [13, 14].

Sensor data processing is needed to be able to provide results that can be used as a benchmark for early warning. Early Warning System (EWS) are widely researched in Indonesia. Several data processing methods have also been tested in previous research [11, 15]. In previous studies, data processing from accelerometers and gyroscopes has been carried out. However, rainfall measurements have not been carried out as one of the indicators for measuring landslide predictions. It was mentioned at the beginning that landslides often occur when there is heavy rain. Therefore, in this study, rainfall sensors will be used in addition to installed sensors to observe soil conditions [16].

The use of machine learning to process sensor data in EWS is now popular. Previous research compared the use of the Support Vector Machine (SVM) and K-Nearest Neighbor (K-NN), which obtained precision below 90% [17]. One of the popular methods for modeling uncertain variables is fuzzy logic to obtain fuzzy sets. The success of fuzzy logic in an early warning system for flood early warning reaching an accuracy of 93.85% [18]. Taking advantage of the success of previous research using fuzzy for flood early warning systems, this research will use fuzzy for landslide early warning systems. Fuzzy logic is well suited to parameterizing sensors in EWS for landslides because it can handle uncertainty and imprecision in sensor data. In landslide prediction, factors such as soil moisture, rainfall, and slope angle vary continuously, often nonlinearly. Fuzzy logic allows these variables to be treated with degrees of membership (e.g. "high", "medium", "low") rather than rigid thresholds, allowing for more nuanced and adaptive responses to complex environmental conditions. This makes it more flexible and accurate in uncertain real-world situations [19].

This research uses fuzzy logic to determine fuzzy membership functions. The fuzzy membership function defines the extent to which a value is in a fuzzy set [20, 21]. For example, membership functions for soil moisture, soil drift, and rainfall. This will be a parameter for determining the level of conditions monitored using sensors in the early warning system.

2 Research Method

This research uses three EWS observation nodes, each of which has a function of monitoring soil movement, soil moisture, and rainfall. The device was installed in Bulusan Sub District, Tembalang District, Semarang City, East Java Province. Data were collected in a month, and then selected data will be used to calculate the membership function with a fuzzy method.

2.1 Fuzzy Method

Fuzzy logic is a method that embraces the uncertainty and complexity of the data. Through the fuzzy method, variable values are not only true or false but have values based on between 0 and 1. This method is used in landslide EWS because it is very suitable for systems that require decision making based on uncertain data [22, 23].

2.2 System Design

Design of an EWS for landslides using three sensors, namely a rainfall sensor, a soil moisture sensor and a soil movement sensor as in Figure 1. The created EWS consists of three observation nodes. Each node observes different parameters. Node 1 observes water level, Node 2 observes soil moisture, and Node 3 observes soil movement. All observation nodes are equipped with solar panels as an EWS power source. The solar panels are connected to the Solar Charge Controller (SCC) which functions to regulate and control the flow of electricity from the solar panels to the battery. The SCC ensures that the battery is properly charged and avoids overcharging or deep discharging. Sensor data at each point are read and processed by raspberry pico. The results are displayed via LCD on EWS and are also sent to the database.

Landslide EWS data are processed using raspberry pico and fuzzy logic algorithms. The processed data are sent using the Internet to the user interface on the website. The flow chart system shown in Figure 2.

2.3 Membership Function Logic

To formulate a membership function, we can use mathematical forms commonly used in fuzzy logic, namely triangles or trapezoids [24]. This membership function converts the input value (measured rainfall) into a degree of membership in each category (low, medium, high).

2.3.1 Triangle Membership Function

The triangular membership function has the following general form in Figure 3 [24].

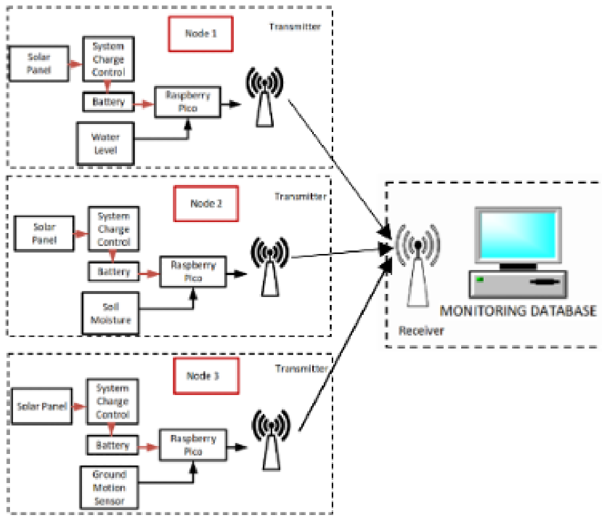

Figure 1: Landslide disaster EWS.

a: starting point (start) of the membership function.
b: peak point (peak) of the membership function.
c: end point (end) of the membership function.

2.3.2 Trapezoidal membership function

The trapezoidal membership function has the following general form in Figure 4 [24].
a: left starting point (left start).
b: left peak point.
c: right peak point.
d: right end point.

The membership function created for the flood disaster system consists of several sensor classification data. These data are taken from real-time testing so that the minimum and maximum values are found. This value is used to divide and classify the state of a sensor.

3 Results

Sensor data is collected in the database of the website, where it can be processed and classified. This data is taken on a laboratory scale. Rainfall sensors are installed in the observation area, and soil movement and soil moisture sensors are embedded in the soil. Rainfall sensors and landslide EWS are shown in Figure 5.

Rainfall sensor readings compared to beaker glass. The picture of the LCD display on the EWS and the beaker glass is shown in 6. These data are contained in Table 1.

1. Rain Gauge

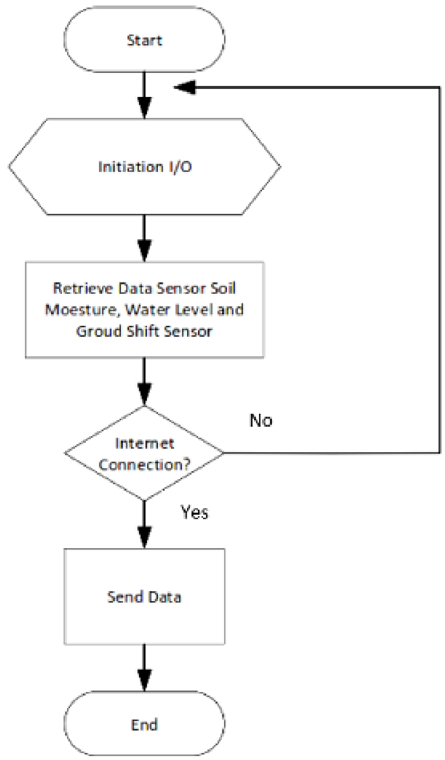

Figure 2: Flowchart of the landslide EWS.

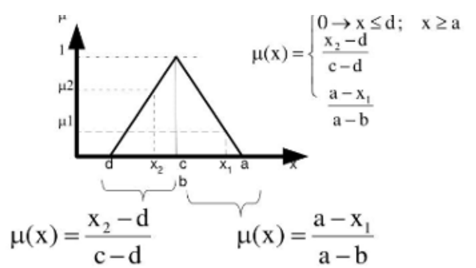

Figure 3: Triangle membership function.

$$\text{Low} : \mu L(x) = \begin{cases} 1 & x \leq 8 \\ \frac{16-x}{8} & 8 < x < 16 \\ 0 & x \geq 16 \end{cases} \tag{1}$$

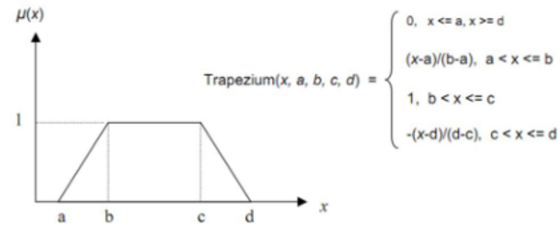

Figure 4: Trapezoid membership function.

Figure 5: Rainfall sensor and landslide EWS.

$$\text{Medium} : \mu M(x) = \begin{cases} 1 & x \leq 8 \\ \frac{x-8}{8} & 8 < x < 16 \\ \frac{16-x}{34} & 16 < x < 50 \\ 0 & x \geq 50 \end{cases} \tag{2}$$

$$\text{High} : \mu H(x) = \begin{cases} 0 & x \leq 50 \\ \frac{x-50}{30} & 50 < x < 80 \\ 0 & x \geq 80 \end{cases} \tag{3}$$

2. Soil Moisture

$$\text{Dry} : \mu D(x) = \begin{cases} 1 & x \leq 30 \\ \frac{50-x}{20} & 0 < x < 50 \\ 0 & x \geq 50 \end{cases} \tag{4}$$

$$\text{Normal} : \mu N(x) = \begin{cases} 1 & x \leq 30 \\ \frac{x-30}{20} & 30 < x < 50 \\ \frac{70-x}{20} & 50 < x < 70 \\ 0 & x \geq 70 \end{cases} \tag{5}$$

(a) (b)

Figure 6: Rainfall measured by using (6a) beaker glass and (6b) a sensor displayed at LCD.

$$\text{Wet} : \mu W(x) = \begin{cases} 0 & x \leq 50 \\ \frac{x-50}{20} & 50 < x < 70 \\ 0 & x \geq 70 \end{cases} \tag{6}$$

3. Soil Movement

$$\text{Stable} : \mu S(x) = \begin{cases} 1 & x \leq 0.5 \\ \frac{1-x}{0.5} & 0.5 < x < 1 \\ 0 & x \geq 1 \end{cases} \tag{7}$$

$$\text{Moving} : \mu M(x) = \begin{cases} 1 & x \leq 0.5 \\ \frac{x-0.5}{0.5} & 0.5 < x < 1 \\ \frac{1-x}{0.5} & 1 < x < 0.5 \\ 0 & x \geq 1.5 \end{cases} \tag{8}$$

$$\text{HighMoving} : \mu HM(x) = \begin{cases} 0 & x \leq 1 \\ \frac{x-1}{0.5} & 1 < x < 1.5 \\ 1 & x \geq 1.5 \end{cases} \tag{9}$$

Based on data obtained from the rain gauge sensor, soil shifts, and soil moisture in the field. In the first data it was found that the rainfall intensity was 11.7, the soil moisture was 81.4, and the ground movement was 0.1 so the risk of landslides was low, while in the data 2 to 8 the rainfall intensity was $x \geq 12$ mm, the humidity $\geq 90\%$ and the ground movement. $x \geq 0.1$ means the risk of landslides is at the medium level.

Table 1: Landslide risk data

No.	Rainfall (mm)	Soil Moisture (%)	Soil Movement (mm/day)	Landslide Risk	Risk Value
1	11.7	81.43	0.1	LOW	0.5375
2	12.2	93.43	0.2	Medium	0.5250
3	12.7	97.89	0.1	Medium	0.5875
4	13.0	93.43	0.1	Medium	0.6250
5	13.3	96.95	0.3	Medium	0.6625
6	14.0	98.29	0.5	Medium	0.6625
7	15.0	99.00	0.5	Medium	0.7500

4 Discussion

In Table 1, it is found that the first data produce the decision that the risk of landslides is low and the risk value is 0.5375. This decision on real-time data is in accordance with the results of manual calculations as follows.

1. Rain Gauge Sensor: 11.7mm
   - Low: $\mu L11.7$ = 0.5375
   - Medium: $\mu M11.7$ = 0.4625
   - High: $\mu H11.7$ = 0.4625
2. Soil Moisture: 81.43%
   - Dry: $\mu D81, 43$ = 0
   - Normal: $\mu N81, 43$ = 0
   - Wet: $\mu W81, 43$ = 1
3. Soil Movement: 0.1 mm
   - Stable: $\mu S0.1$ = 1
   - Moving: $\mu M0.1$ = 1
   - High Moving: $\mu HM0.1$ = 1

Next, in measuring the risk value, Mamdani inference is used.

- Rain Gauge Low: 0.5375
- Rain Gauge Medium: 0.4625
- Soil Moisture Wet: 1
- Soil Movement Stable: 1

Based on the member shift function, it is obtained

- Low risk
  Min (0.5375,1,1) = 0.5375
- Medium risk
  Min (0.4625,1,1) = 0.4625

Based on these results, the maximum data value was taken, namely 0.5375, thus the selected result was low risk. The first data in the table are in accordance with manual calculations. After that, match the third real-time data with the calculation results.

1. Rain Gauge Sensor : 12.7 mm
    - Low: $\mu L12.7$ = 0.4125
    - Medium: $\mu M12.7$ = 0.5875
    - High: $\mu H12.7$ = 0
2. Soil Moisture: 97.89%
    - Dry: $\mu D97.89$ = 0
    - Normal: $\mu N97.89$ = 0
    - Wet: $\mu W97.89$ = 1
3. Soil Movement: 0.1 mm
    - Stable: $\mu S0.1$ = 1
    - Moving: $\mu M0.19$ = 1
    - High Moving: $\mu HM0.1$ = 0

Next, in measuring the risk value, Mamdani inference is used.

- Rain Gauge Low: 0.4125
- Rain Gauge Medium: 0.5875
- Soil Moisture Wet: 1
- Soil Movement Stable: 1

Based on the member shift function, it is obtained

- Low risk
  Min (0.5375,1,1) = 0.5375
- Medium risk
  Min (0.4625,1,1) = 0.5875

Next, we use Mamdani inference to measure the risk value. Based on these results, the maximum data value is taken, namely 0.5875, so the selected result is medium risk. The first data in the table are based on manual calculations.

5 Conclusion

Based on the results of real-time data collection in the landslide disaster early warning system, the results were that the sensors worked well and the communication sending data to the website was running well. Data processing has been carried out and can be processed via a controller with a fuzzy logic algorithm. The results obtained were that, based on sensor data taken early warning of landslides, the risk was still low with a value of 0.5375 and the medium risk was 0.5875. This is due to moderate rainfall and high soil moisture, as well as ground movement ≥ 0.1.

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