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Context Inference Including Cause Reasoning and Prediction

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Abstract

It is not enough to recognize the situations which currently occur simply. The current situations have the causes that they get to occur. The causes can just be generated and they can make the situations like the current states while the ones which occurred in the past have continued. Furthermore, if the causes which made the current situations don't disappear, they can continue to stay the same, get worse, or be changed to another situation. Therefore, limiting the range of context awareness to the situations which currently occur can be insufficient as the system which recognizes situations of the everyday world. Therefore, this study aims at problem-solving of two things. First, it recognizes situations without advance information. Second, it infers causes of situations and predicts how the situations will turn out in the future. To solve these problems, this study uses multiple sensor data fusion together using Dempster-Shafer Evidence Theory (DST) and Kalman Filter (KF). It recognizes situations under the conditions without any advance information through DST, infers causes of the current situations, and predicts how the current situations will turn out in the future. At this moment, BPA is important to recognize situations through DST and infer causes and state transition equation plays an important role in predicting arrangement through KF. The study carries out context inference and cause inference using DST. It describes the plan which infers causes of situations without advance information. It calculates required state transition equation to predict the progress of the research and infers how the causes revealed through DST by using it will arrange the current situations in the future by using KF.

***Key Words**: Context inference, protection wall, Kalman filter*

1. Introduction

There have been active studies of inferring the context. Most of them focus on recognizing what is happening currently. However, there is the need to understand the cause of the situation and predict how the situation will develop in the future. In the real word, there are many cases that should not occur. Accidents or crimes should never occur. It is important to grasp the signs of the accident before the accident occurs and to understand how the dangerous situation will develop by which cause when the sign of the accident is grasped.

This paper describes the ration measures to infer the cause when the sign of dangerous situation is detected and to predict how the situation will develop when the cause is not eliminated. We will use the risk of collapse of the landslide protection wall in a construction

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site to estimate the cause when the tilting or deformation of the landslide protection wall is detected and to predict how the risk will increase when the cause is not eliminated or problem is corrected. Collapse of the landslide protection wall is an accident that can cause great damage as it will cause not only the significant property damage but also the loss of manpower in the site. When the problem of the landslide protection wall in a large construction site is detected, it is difficult to disassemble the wall to find the cause and it may take a long time to eliminate the cause and solve the problem even after the cause is discovered. Therefore, there must be a way to predict how the landslide protection wall problem will develop during the delay until the cause is eliminated.

To solve such problems, this study infers the cause using the data fusion of heterogeneous values. The correlation between the earth pressure, water pressure, content load, and wall deformation, all of which are estimated to be the factors of deformation of the landslide protection wall, is studied and used to obtain the equation of state. Based on the measured values, the basic probability assignment is determined and the deformation factors are estimated based on it. After the causes are inferred, how the situation will develop in the future by each cause is estimated. For that, the Markov chain and Kalman filtering are needed. We can use the Kalman equation to predict the risk increase trend of the landslide protection wall.

We propose the measures of determining the basic probability assignment to infer the cause of the dangerous situation and obtaining the equation of state to predict the progression of the dangerous situation. This paper is organized as follows: Chapter 2 describes the related studies and Chapter 3 presents the proposed measures of cause inference and progression prediction. Chapter 4 describes the test and evaluation and Chapter 5 presents the conclusion.

2. Related Works

2.1 Data Fusion and Context Inference

There have been many attempts to obtain better context data by data fusion of heterogeneous data in order to achieve the goal of obtaining the highly accurate information. As there are many factors and elements affecting the situation in the real world, the use of multi-sensors having different functions have been studied in various fields. It began with the study of using the multi-sensors to estimate the position of the launched missile. The study has been extended since then to position estimation of unmanned aircraft as well as the moving vehicles on the ground. In robot control, the studies of using the multi-sensors to obtain the information needed for robot control or to recognizing the robot status have been ongoing. Sensors were attached to various areas of the robot to acquire the data needed to monitor the robot status and control the robot, and data fusion was used to increase the accuracy of robot information. Data fusion of multi-sensors is also used for inferring the cause of the specific context. Rakowsky proposed the measures to estimate the system error using the Dempster-Shafer theory [1]. The factors of the cause of the context were inferred by calculating the *belief* and *plausibility* of each significant element from BPA and then calculating the *uncertainty*.

2.2 Context Progression Prediction

Kalman equation was first used to estimate the position of the missile. Since then it was extended to position estimation of unmanned aircraft as well as the moving vehicle on the ground [3, 4, 5]. It is mostly used for fusion of electronic data on the ground. By repeating the steps of checking the gap between the theoretical value and actual measurement, calculating the estimated position by considering it, and then comparing it with the actual measurement to calculate the gap again, the position can be estimated even when it is not measured [6, 7]. Since then, its application has been expanded to extended Kalman equation to be used in various fields [8].

Existing context awareness focuses on recognizing the current situation. It is to understand which events are occurring. In many cases, we are interested in knowing what caused the current situation. Moreover, we are also interested how the current situation will develop in the future. Existing studies did not describe the cause and progression of the result in details. Although the method of using the Kalman equation enables estimation of the past, present, and future, its recognition scope is limited to the position. Therefore, investigating the relation of the past, present, and future in various contexts in addition to position estimation is needed.

3. Cause Inference and Progression Prediction

Context awareness must be able to recognize not only the current situation but also infer the past cause and predict the future if the current situation is continued. Current situation can be considered as the result of past causes. Recognizing the current situation and finding the cause of the current happening is the important issue of context awareness. Then how the current situation will develop? That is also an important issue.

Cause inference: Inference of the causes which cause the current situations is helpful for recognizing the past related to the present. The theory of probability and the theory of evidence can be used to see the phenomena shown now and infer the causes. Bayesian theorem expresses the probability about occurrence of evidence and events. When a certain evidence/phenomenon appears, the probability that events happen due to it was expressed. However, Baeysian theorem is not enough to express accidents of the everyday world because it expresses unknown and ambiguous things as the probability that they never happen. Dempster-Shafer's theory of evidence is useful as the probability theory which can show uncertainty of the everyday world [9]. DST showed the probability that events related to certain evidence and phenomena occur when they appear as reliability, probability, and uncertainty [10]. The reliability shows the probability that applicable events occur when evidence appears and the uncertainty section shows the ambiguous section. It can show the probability that the events can conditionally occur.

DST is the theory of probability which expresses uncertainty. But if this mathematical theory is utilized, a clue to infer the causes of the current situations can be obtained by processing the data collected from multiple sensors [11, 12, 13].

If the sensors used in USN detect and report event occurrence, they consider the data that they grasp as evidences and they compose the group which makes each case made by their combination elements. This group is called Power Set and its elements are done Focal Elements. Belief and plausibility of the focal elements can be calculated by calculating mass function of each focal element and the mass functions. The belief values are the ones that the applicable focal elements must be involved in the situations which now occur. The plausibility is the values of comprehensive possibility that the focal elements may be involved in the current situations. Therefore, there are differences between the plausibility and belief values and the differences are defined as uncertainty. Like this, the causes about the current situations can be inferred by utilizing DST. First, Power Set and Focal Element should be set from the measured values sent by sensors. If the sensors related to situations are adopted, this problem can be easily solved. Adoption of temperature sensors and humidity sensors will be reasonable to detect fires. Ultrasonic sensors are good to detect approach of other objects. And plural infrared ray sensors will be reasonable if approaching objects are organisms.

Basic probability assignment of focal elements is calculated based on evaluation about the values that the sensors measure and report in the environment that the sensors are closely connected to focal elements like this. This is valid on the assumption that there are the relationship between sensors and focal elements and between situations and them. Cause inference in USN can be a meaningful procedure because BPA mathematically define the relationships between sensors and focal elements and context composition. There are a lot of considerations about the plans which decide BPA. The plan itself is an important issue. The plans which decide BPA in USN can be variously considered. BPA depends on target situations. Because the study discussed the goal to try to recognize the situations without advance information, BPA is calculated based on the rate of change by time of measured values of sensors. However, the goal of the study is to expand the range of context awareness to inference of the 'causes of the past' and 'prediction of the future progress', the method to calculate BPA is not discussed in detail.

The values of BPA decided to be granted to each focal element are 0 to 1. And the sum of BPA of all the focal elements is 1. DST fusion calculation is done in BPA granted to each focal element. The *belief* and *plausibility* by focal element gotten from calculation are calculated. If it is expressed as a formula, it is shown as follow:

$$belief(A) = \sum_{\mathrm{x} \subset \mathrm{A}} \mathrm{m(X)}, for\ all\ A \subseteq \theta$$

$$Plausibility(A) = 1 - \sum_{\mathrm{E_k} \cap \mathrm{A} = \phi} \mathrm{m_i}\,(\mathrm{E_k})$$

If the *belief* and *plausibility* of each focal element are calculated, *uncertainty* can be calculated as follow: *uncertainty* = *plausibility* - *belief.*

The final state which infers the causes of the current situations is to compare the *belief* and *uncertainty* of each focal element with each other. The focal element whose *belief* is highest is the cause of the current situation. If there are several focal elements whose *belief* is the same or similar with each other, the one whose *uncertainty* is lowest can be selected. This is the method to infer the causes which most affect the current situations.

Progression Prediction: Although the current emergency situation must be immediately dealt with, there may be the cases in which the prompt countermeasures are difficult. There can be the cases of having to predict how the current dangerous situation will develop when it will take some time to prepare the countermeasures or when high cost of the emergency measurement may delay the countermeasures. To predict such progression, the equation of state representing the relation between the dangerous situation and the inferred cause of the situation is needed. When the equation of state is obtained, we can predict future progression using the Kalman equation.

The Kalman equation is the algorithm which recursively got estimate values of exact system state variables and the measuring equation are required to compose Kalman filters.

$$x_{k+1} = A_k x_k + w_k$$
$$z_k = H x_k + v_k$$

Where, x_k is the state variable of motional models, A_k is the State Transition Matrix, z_k is the output variable, and are the zero-mean values and white noise vectors which are not involved in each other as each covariance is expressed as .

The result of the Kalman filter equations based on the above system model is composed as follow:

Kalman Filter Algorithm

State estimate update
$\widehat{x_k} = \overline{x_k} + K_t(z_k - H\overline{x_k})$
Error covariance update
$P_k = (I - K_t H)\overline{P_k}$
Kalman gain matrix
$K_t = \overline{P}_t H^T (H\overline{P}_t H^T + R)^{-1}$
State estimate prediction
$x_t = A_t x_t - 1$
Error covariance prediction
$\overline{P_{t+1}} = A_t P_t A_t^T + Q_t$

Multiple sensor data fusion through the Kalman equation was used in orbit inference of mobile projectiles such as guided missiles and unmanned vehicles. Recently, the Kalman equation was utilized in convergence of the measured information that each sensor which is located in distributed networks transmits [Jorge Cortes]. These existing studies are helpful for correcting data and errors lost in radio sensor networks made by the multiple sensors distributed in the wide areas and making sensing data be matched. This paper predicts how the causes which grasped by using the expanded Kalman equation will arrange the current situations in the future. For this, the state equation is required. Establishment of the state transition equation to predict the cause grasped by using DST is the important measure to utilize the Kalman equation. This paper wrote the state transition equation about the factors grasped as follow.

$$A = \begin{bmatrix} \frac{\partial f_1}{\partial P_1} & \frac{\partial f_1}{\partial P_2} & \frac{\partial f_1}{\partial \theta} \\ \frac{\partial f_2}{\partial P_1} & \frac{\partial f_2}{\partial P_2} & \frac{\partial f_2}{\partial \theta} \\ \frac{\partial f_3}{\partial P_1} & \frac{\partial f_3}{\partial P_2} & \frac{\partial f_3}{\partial \theta} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ \frac{Acos\theta}{k} & \frac{Acos\theta}{k} & \theta \end{bmatrix},$$

This paper proposed the plans to infer the causes which cause the current situations and the method to predict how the current situations will be developed by the main causes which cause the present situations. The next chapter takes tests and verifies the suggested methods by applying them to it.

4. Evaluation

Context inference with measurement of inclination of the landslide protection wall and signals detected by multi-sensors indicated that the cause was the increase of the earth pressure caused by increasing underground water level. After analyzing the relation between the level of inclination of the landslide protection wall and increase of earth pressure due to increasing underground water level, the relation between the level of inclination of the landslide protection wall and underground water level increase after some time later was again calculated. Such relation was substituted in the Kalman equation to estimate how the landslide protection wall tilting will progress.

The relation between the factors of the force applied to the landslide protection wall and tilting of the landslide protection wall in a construction site can be described as follows:
F is the restitution force by elasticity of the landslide protection wall so that the wall will not collapse. This force is applied perpendicularly to the landslide protection wall.

$$F = -k\theta$$

where θ is the inclination angle of the protection wall while, k is the coefficient of the material of the wall material.

The factors of the force applied to the landslide protection wall includes the earth pressure, water pressure from the raised underground water level, and content load pressure applied to the soil of the landslide protection wall. The figures below show these factors.

First, the earth pressure is the area of the triangle in the figure. Its pressure and load increase as the height decreases. The earth pressure can be expressed by

$$P_a = (q + \gamma_z)\,tan\left(\frac{\pi}{4} - \frac{\emptyset}{2}\right) - 2c\,tan\left(\frac{\pi}{4} - \frac{\emptyset}{2}\right)$$

The earth pressure in the opposite side of the landslide protection wall can be expressed by

$$P_p = \gamma_z\,tan^2\left(\frac{\pi}{4} + \frac{\emptyset}{2}\right) + 2c\,tan\left(\frac{\pi}{4} + \frac{\emptyset}{2}\right)$$

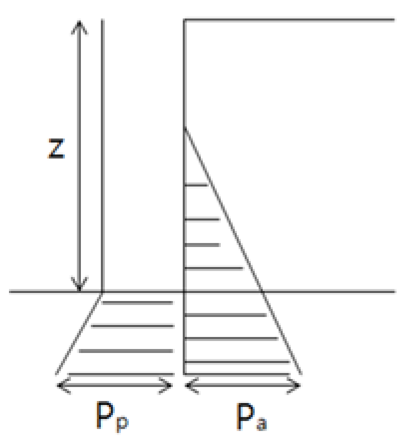

Figure 1. Earth pressure

Water pressure increase by the underground water penetrating into the soil as the underground water level increases is another pressure factor applied to the landslide protection wall. The pressure by increasing underground water level is defined as follows.

$$P_2 = \frac{1}{2}k_0\gamma H_1^2 + k_0\gamma H_1 H_2 + \frac{1}{2}(k_0\gamma^2 + \gamma_0)H_2^2$$

where $\frac{1}{2}k_0\gamma H_1^2$ is the earth pressure to the depth H.

$k_0\gamma H_1 H_2 + \frac{1}{2}k_0\gamma_0 H_2^2$ is the earth pressure from H_1 to H_2, and $\frac{1}{2}k_0\gamma^2 H_2^2$ is the earth pressure when the water is full.

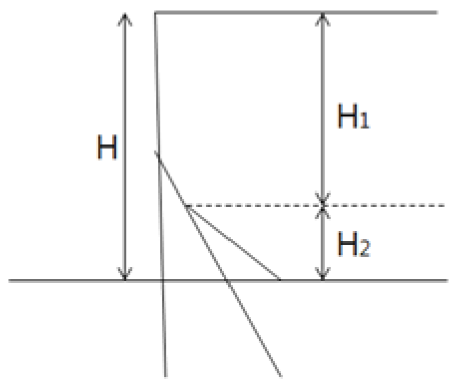

Figure 2. Water pressure

When the concentrated load is applied as shown in the figure below, Q_p represents the size of the concentrated load. Assuming X to be the distance between the landslide protection wall and the point of concentrated load and H to be the depth of the landslide protection wall, *X=mH*.

The depth z is expressed by multiplication of H and variable n as *z=nH*.

Since the pressure changes according to the depth as shown in the figure, the micro pressure can be obtained by definite integral as follows:

$$P_3 = \int_0^H P_H \, dz$$

Since the pressure is 0 and the concentrated load has the maximum value on the earth surface, it can be expressed by following function.

$$P_3 = Q_p \int_0^H z \cdot X^{-z} \, dz = Q_p \int_0^H nH^2 \cdot (mH)^{-nH} \, dn$$
$$= Q_p \int_0^H H^2 \cdot (mH)^{-nH} \, ndn$$

$$= Q_p \cdot H^2 \cdot \left[(mH)^{-nH} - n(mH)^{-nH} \cdot \frac{1}{ln(mH)}\right]_0^H$$
$$= Q_p \cdot H^2 \cdot \left[(mH)^{-H^2} - H(mH)^{-H^2} \cdot \frac{1}{lnH^2}\right]$$
$$= Q_p \left(H^2 - \frac{H}{2lnH}\right)(mH)^{-H^2}\left(\frac{t}{m^2}\right)$$

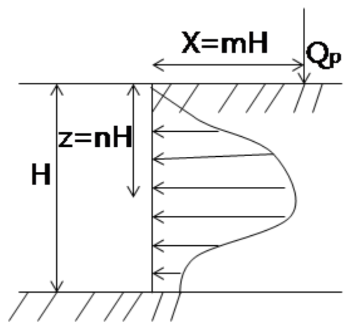

Figure 3. Concentrated load

In other words, the pressure is directly proportional to the applied load and has the negative correlation with the distance from the landslide protection wall.

If the landslide protection wall is inclined, the weight of the soil and wall is applied as the load according to the inclination angle.

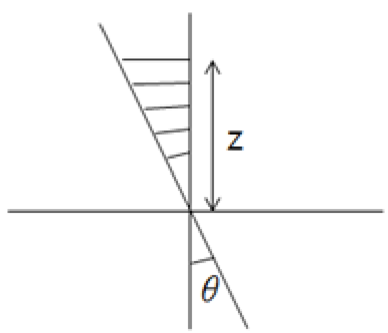

Figure 4. Protection wall cline angle

The volume of the soil is $\frac{1}{2}z^2\, tan\,\theta \cdot A$.

Since the unit weight is γ , the load can be expressed as $\omega + \frac{1}{2}z^2\gamma\, tan\,\theta \cdot A$ (where ω is the weight of the landslide protection wall and A is the cross sectional area).

The force applied to the soil load is

$$\left(\omega+\frac{1}{2}z^2\gamma\tan\theta\cdot A\right)g$$

(where g is the gravitational acceleration).

Decomposing with forces applied perpendicularly to the landslide protection wall, the pressure can take $cos\theta$ and soil load can take $sin\theta$. Thus, it can be defined as

$$k\theta=\left(\omega+\frac{1}{2}z^2\gamma\tan\theta\cdot A\right)g\cdot\sin\theta+(P_a+P_2-P_p)\cos\theta\cdot A\ .$$

A can be converted to force by multiplying the pressure by the area. Assuming that the landslide protection wall is completely flat without deformation, all applied forces can be expressed in terms of θ. Since it the flat surface without curvature, the pressure and load can be converted to the vectors perpendicular to the surface.

$F=-k\theta$ (where k is elastic coefficient)

Since $-k\theta=\sum PA$ (where A is the cross sectional area) at the critical angle θ, it can be defined as

$$k\theta=\frac{1}{2}\gamma gz^2\tan\theta\sin\theta\cdot A+\sum PA\cos\theta$$

where $k\theta$ is the force applied the wall, $\frac{1}{2}\gamma gz^2\tan\theta\sin\theta\cdot A$ is the force pressed by the soil in the inclined area, and $\sum PA\cos\theta$ is the sum of the force by the water pressure and earth pressure.

γ is unit mass and P_3 is content load meaning the pressure from the force pressed by the construction material or large trucks. Therefore,

$$\sum PA\cos\theta=A\cos\theta\,(P_1+P_2+P_3)=$$
$$A\cos\theta(P_a-P_p+\frac{1}{2}k_0\gamma H_1^2)+k_0\gamma H_1H_2+\frac{1}{2}(k_0\gamma^2+\gamma_0)H_2^2+P_3$$

where z is the depth from the earth surface and constant not varying even when the wall is inclined and the wall is assumed to be completely flat with inclination of θ.

The obtained equation of state can be substituted in the Kalman equation to estimate how the current situation will develop. It can predict how the landslide protection wall that began tilting will incline more as well as the time when the wall collapses after continuing tilting. By predicting the time left before the wall collapses, the landslide protection wall can be supplemented or people can be evacuated by the estimated time.

We have to adopt the extended Kalman filter because of the state equation of θ is non-linear.

$$X_k = \begin{cases} P_1 \\ P_2 \\ \theta \end{cases}$$

P_1: earth pressure, P_2: water pressure, θ:cline of the protection wall

Non-linear function *F(X)* can express as follows.

$$f(x) = \begin{bmatrix} P_1 \\ P_2 \\ \frac{1}{K}\left[\left(\omega + \frac{1}{2}z^2 tan\theta \cdot A\right) gsin\theta + (P_1 + P_2)cos\theta \cdot A\right] \end{bmatrix}$$

$$X_{k+1} = Ax_k + \omega_k$$

$$z_k = Hx_k + v_k$$

Transfer matrix A is

$$A = \begin{bmatrix} \frac{\partial f_1}{\partial P_1} & \frac{\partial f_1}{\partial P_2} & \frac{\partial f_1}{\partial \theta} \\ \frac{\partial f_2}{\partial P_1} & \frac{\partial f_2}{\partial P_2} & \frac{\partial f_2}{\partial \theta} \\ \frac{\partial f_3}{\partial P_1} & \frac{\partial f_3}{\partial P_2} & \frac{\partial f_3}{\partial \theta} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ \frac{Acos\theta}{k} & \frac{Acos\theta}{k} & \theta \end{bmatrix}$$

$$\theta = \frac{1}{k}\left[\omega gcos\theta + \frac{gz^2 A}{2} \cdot \frac{(2cos\theta + sin\theta)sin\theta}{cos\theta} - (P_1 + P_2)Asin\theta\right]$$

H matix for the Z_k is,

$$H = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & \frac{1}{(20° - \theta)k\Delta t} & \frac{1}{(20° - \theta)k\Delta t} \end{bmatrix}$$

$$Z_k = \frac{1}{T}$$

So, $T = \frac{1}{Z_k}$, T is the remaining time to collapse.

We can get the left time from the Kalman filter with the state equation that addressed in former chapter. Following Table 1 shows the result of prediction.

Table 1. Result of prediction

P1(N/m2)	P2(N/m2)	Theta(dgrees)	remaing time
10	5	0.00	_
11	7	10.06	19.77
12	9	14.83	10.46
13	13	17.19	6.53
14	15	18.43	4.25
15	17	19.10	2.83
16	19	19.47	1.90
17	18	19.70	1.24
18	15	19.81	0.85
19	13	19.86	0.73
20	12	19.87	0.73
21	7	19.88	0.75
22	2	19.84	1.04
23	4	19.78	1.52
24	5	19.78	1.64
25	7	19.80	1.60
26	9	19.84	1.37
27	14	19.89	1.00
28	21	19.97	0.27
29	24	20.09	-0.91
30	25	20.19	-2.00
31	26	20.26	-2.87
32	28	20.32	-3.63
33	30	20.38	-4.47

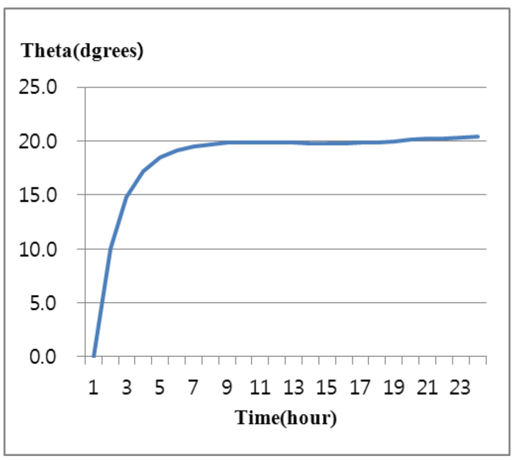

Figure 5. Prediction of protection wall cline

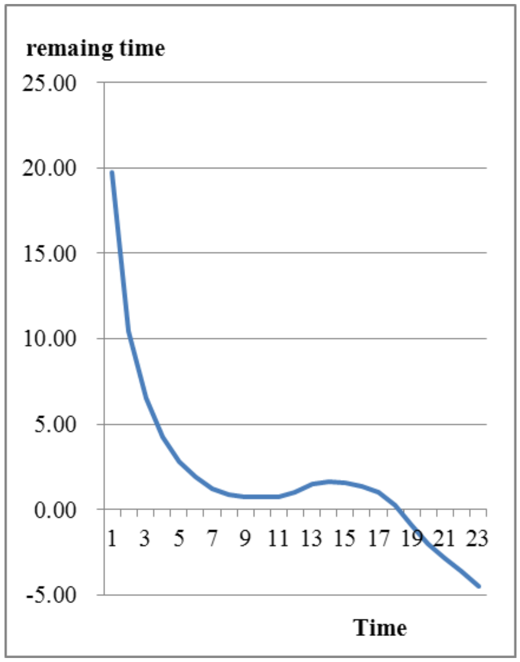

Figure 6. Remaining time to collapse of the wall

We can predict 19.77 hours remained until the protection wall breaking. In this experiment, P_3 refers to the truck up to top of the wall is pressed. P_3 is not working in this case. The active pressures are earth pressure and water pressure that were main cause of the wall cline.

The test confirmed that the method proposed in this paper can be useful in real world situations.

5. Conclusion and Further Study

The scope of context awareness should not be limited just to which situation is currently occurring. This study proposed the measures of not only recognizing the current situation but also inferring the cause of the current situation and evaluating the impact of the cause to the current situation to predict how the situation will develop. It inferred the cause of tilting of the landslide protection wall applying the multi-sensor data fusion using DST. It then analyzed the relation between the estimated cause and the landslide protection wall and used it to Kalman equation to predict future situation. When the current situation has significant risk, the cause can be estimated and used to eliminate the cause. If the dangerous situation cannot be immediately dealt with, it can predict the future progression to estimate how much time can be given for countermeasures. Although the scope of the context inference could be extended, it was based on measuring and evaluating the signal changes. Therefore, studies of linking the model with the information obtained in advance would be needed.

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References

[1] U. Rakowsky, “Fundamentals of Dempster-Shafer theory and its applications to system safety and reliability modeling”, International journal of reliability, quality, and safety engineering, vol. 14, no. 6, **(2007)**, pp. 579-602.

[2] S. McKeever, J. Ye, L. Coyle and S. Dobson, “Using Dempster-Shafer Theory of Evidence for Situation Inference”, Smart Sensing and Context Lecture Notes in Computer Science, vol. 5741, **(2009)**, pp. 149-162.

[3] W. Y. Kang, K. J. Kim and C. G. Park, “Performance analysis of in-flight alignment using UKF”, Journal of Institute of Control, Robotics and Systems, vol. 12, no. 11, **(2006)**, pp. 1124-1129.

[4] Q. Gan and C. J. Harris, “Comparison of Two Measurement Fusion Methods for Kalman-Filter Based Multisensor Data Fusion”, IEEE Trans. Aerospace and Electronic Systems, vol. 37, no. 1, **(2001)**.

[5] Y. Choi, K. Kim, J. Choi and S. Lee, “Laser Image SLAM based on Image Matching for Navigation of a Mobile Robot”, Journal of the Korean Society of Precision Engineering, vol. 30, no. 2, **(2013)**, pp. 177-184.

[6] J. Seung, D. Lee, J. Ryu and G. Jungn, “Precise Positioning Algorithm Development for Quadrotor Flying Robots Using Dual Extended Kalman Filter”, Journal of institute of control, robotics and systems, vol. 19, no. 2, **(2013)**, pp. 158-163.

[7] J. Joo, “Multi-Small Target Tracking Algorithm in Infrared Image Sequences”, Journal of the institute of signal processing and systems, vol. 14, no. 1, **(2013)**, pp. 33-38.

[8] C. Zong, D. Hu and H. Zheng, “Dual extended Kalman filter for combined estimation of vehicle state and road friction”, Chinese Journal of Mechanical Engineering: the official journal of the Chinese Mechanical Engineering Society, vol. 26, no. 2, **(2013)**, pp. 313-324.

[9] D. H. Suh, J. H. Song and K. S. Oh, “Context Inference for Predicting Cause of Protection Wall Deformation”, International Journal of Smart Home, vol. 6, no. 2, **(2012)**, pp. 109-114.

[10] Y. O. Han and D. H. Suh, “Multi-sensor Data Fusion with Dynamic Component for Context Awareness”, International Journal of Smart Home, vol. 6, no. 6, **(2012)**, pp. 107-116.

[11] Y. C. Ngeow, A. K. Mustapha, E. Goh, H. K. Low and D. Chieng, “Context-aware Workflow Management Engine for Networked Devices”, International Journal of Multimedia and Ubiquitous Engineering, vol. 2, no. 4, **(2007)**, pp. 33-48.

[12] J. B. Kim, W. J. Lee, K. J. Oh, S. S. Kim and H. J. Choi, “Advanced Extreme Learning Machine Modeling using Radial Basis Function Network and Context Clustering”, International Journal of Smart Home, vol. 6, no. 3, **(2012)**, pp. 49-56.

[13] Q. Liu, N. Linge and F. Gao, “A Context-aware Protocol for Location Discovery Exchange in a Ubiquitous Environment”, International Journal of Multimedia and Ubiquitous Engineering, vol. 7, no. 2, **(2012)**, pp. 177-182.

