MKRVM Prediction of Capacitive RF-MEMS Switching Life

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Abstract. The elastic coefficient $K$, a factor affecting the life of capacitive RF-MEMS switch, is selected as the research object. First, we use differential evolution based quantum particle swarm optimization (DE-QPSO) to obtain sparse functions of multiple kernel relevance vector machine (MKRVM), and use the MKRVM algorithm to predict the lifetime of such switches. Then the experimental results show that the method can obtain the health index HI of $3.1043\times10^6$ s, the $3.0657\times10^6$ s closest to the original data in 0.21 s. At the same time, the conclusion of the longest switching life is obtained when the elastic coefficient is in the range of 4-16 N/m.

1. INTRODUCTION
RF-MEMS is a small mechanical device or system made by borrowing microelectronic processing technology. Now, RF-MEMS technology has been applied in many fields, especially in the military and civil fields [1-3]. But, RF-MEMS research is difficult. RF-MEMS the reliability of the device is related to the development efficiency the development cost of the product itself and its practical use. In the field of industrial applications, the failure of devices [4-6] may bring huge economic property losses and even threaten the safety of relevant staff [7-8]. The study of the reliability of RF-MEMS switch mainly lies in the analysis of its failure mode and failure mechanism and life prediction [9-10].

A typical capacitive RF-MEMS switch is selected as the research object, the MKRVM to predict the life of the switch [11-12]. The residual life of capacitive RF-MEMS switch is predicted. Meanwhile, DE-QPSO [13-14] is used to optimize the sparse weights in the kernel function in the MKRVM to improve the accuracy of switching life prediction.

2. APACITIVE RF-MEMS SWITCH
From the working principle of the above switch, it can be seen that the life of the capacitive RF-MEMS switch is related to the bias voltage at both ends and the dielectric charging effect. The bias voltage will not only affect the impact velocity of the movable film, but also affect the internal electric field of the dielectric layer, which will have a certain effect on the life of the switch. Based on the analysis of the failure mechanism, the factors affecting the residual life of the switch are studied, and MATLAB software is used to analyze the effect of charging effect on the switching life.

From the research of other related papers, we can see that the failure of MEMS switch is mainly caused by charging failure [7], and the principle is shown in Fig.1:

When the film is pulled down, the electric field is near the critical breakdown value, which leads to polarization and dielectric leakage current. Adhesion failure occurs when the charge of the leakage...
current is captured by the trap in the dielectric layer and the capture voltage is greater than $V_{\text{pull-out}}$. While the polarization charge and the trapped leakage current charge when the interface produces polarization phenomenon result in the existence of accumulated charge. Thus the charge distribution when the switch fails is shown in Fig. 2.

Where $\sigma_1$ is used to represent the charge density in the movable bridge film, $\sigma_2$ represents the charge density in the dielectric, $\sigma_3$ is charge density in CPW wires, $\varepsilon_1$ is the relative dielectric constant of the dielectric, $V_1 - V_2$ is the bias voltage, $E_1 - E_2$ is the electric field distribution, $t$ is working hours for switches, $\zeta$ is duty cycle for driving signal, $\eta$ is dielectric charge capture factor, $\varepsilon_r$ representing the relative permittivity, $U$ is the sum of the applied voltage and $U_{\text{RF}}$ is the RF voltage, and $S$ is the area facing the plate.

As the elastic resilience of the movable bridge film is expressed as (1), (2) is electric-field distribution, (3) is

\[
F = Kx = K(g_0 - t) \quad (1)
\]
\[
E = \varepsilon_r \times \frac{V}{2t} \quad (2)
\]
\[
q = CV = \frac{\varepsilon_0 \varepsilon_r}{t} \times U \quad (3)
\]
\[
J_{FP} = \rho_{FP} E_d \exp \left[ \frac{-(E_1 - E_2)}{kT} \right] \quad (4)
\]
\[
J_{\Omega} = \rho_0 \exp \left[ -\frac{E_0}{kT} \right] \times E_d \quad (5)
\]
\[
J = J_{FP} + J_{\Omega} = \rho_{FP} E_d \exp \left[ \frac{-(E_1 - E_2)}{kT} \right] + \rho_0 \exp \left[ -\frac{E_0}{kT} \right] \times E_d \quad (6)
\]
\[
\sigma_p = \zeta \times \eta \times \frac{J}{t} = \zeta \times \eta \times E_d \left[ \rho_{FP} \exp \left[ \frac{-(E_1 - E_2)}{kT} \right] + \rho_0 \exp \left[ -\frac{E_0}{kT} \right] \right] \quad (7)
\]

According to this, the relevant formula for the life of the switch is derived. When the electrostatic force and elastic restoring force are in balance, and further derivation of locking voltage as follow:

\[
K(g_0 - t) = \varepsilon_r \times \frac{U}{2t} \times \frac{\varepsilon_0 \varepsilon_r}{t} \times U \quad (8)
\]
\[
V_{\text{pull-out}} = \sqrt{\frac{2K_{\text{bridge}}}{{\varepsilon_0}^2 t} g_0^2 - V_{\text{RF}}^2} \quad (9)
\]

The life formula of the switch can be obtained from the above formula:

\[
t_{\text{fail}} = \frac{2K_{\text{bridge}}g_0}{\zeta \times \eta \times E_d \left[ \rho_{FP} \exp \left[ \frac{-(E_1 - E_2)}{kT} \right] + \rho_0 \exp \left[ -\frac{E_0}{kT} \right] \right]} \quad (10)
\]

Therefore, it is not difficult to see that the factors that affect the life of the capacitive RF-MEMS switch include the elastic coefficient $K$, the thickness of the dielectric layer $t$, and the distance between the upper and lower plates $g_0$, dielectric constant $\varepsilon$ and so on.

3. THEORY

This paper adopts the method of multi-core learning is MKRVM prediction, which has achieved the purpose of obtaining the optimal selection in a short time and improving the accuracy of prediction.
Assuming a set of training data is \( \{x_i, t_i\}_{i=1}^N \) and \( x_i \) is the input vector, \( t_i \) is the relevant goal vector. The \( t_i \) can be defined as, where \( \omega = (\omega_0, \omega_1, ..., \omega_N) \) is weight vector, \( \delta_i \) is noise.

\[
    t_i = y(x_i; \omega) + \delta_i, \quad \delta_i \sim N(0, \sigma^2)
\]

Assuming \( t_i \) is independent, then all the data can be defined as:

\[
    P(t|\omega, \sigma^2) = (2\pi \sigma^2)^{-N/2} \exp \left\{ -\frac{1}{2\sigma^2} \left\| t - \mu \omega \right\|^2 \right\}
\]

where \( t = (t_1, t_2, ..., t_N)^T, \mu = (\mu(x_1), \mu(x_2), ..., \mu(x_N)) \), \( \mu(x_i) = [1, K(x_i, x_1), K(x_i, x_2), ..., K(x_i, x_N)] \), \( K(x_i, x) \) is kernel function. Maximum likelihood estimates of \( \omega \) and \( \sigma^2 \) may lead to overfitting phenomena. Therefore, zero mean gaussian prior probability distributions are used to constrain these two parameters,

\[
    P(\omega|\lambda) = \prod_{i=0}^n N(\omega_i | 0, \lambda_{i}^{-1})
\]

where \( \lambda \) is \((N+1)\) dimensional hyperparameter vectors.

The posterior probability of whole unknown parameters can be acquired according to Bayesian rules.

\[
    P(\omega, \lambda, \sigma^2|t) \propto P(t|\omega, \lambda, \sigma^2)P(\omega|\lambda) \]

\[
    P(t|\omega, \lambda, \sigma^2) = \int P(t|\omega, \lambda, \sigma^2)P(\omega|\lambda) d\omega \]

\[
    P(t|\omega, \lambda, \sigma^2) = (2\pi \sigma^2)^{-N/2} \exp \left\{ -0.5(\omega - \varphi)^T \right\}
\]

where \( \varphi = \sigma^{-2} \Sigma \mu^T t, \Sigma = (\sigma^{-2} \mu^T \mu + A)^{-1}, A = (\lambda_0, \lambda_1, ..., \lambda_N) \). \( P(t|\lambda, \sigma^2) \) can be defined as a unified hyperparameter as expressed in formula (18).

\[
    P(t|\lambda, \sigma^2) = \int P(t|\omega, \sigma^2)P(\omega|\lambda) d\omega = (2\pi)^{-N/2} |\Sigma|^{-1/2} \exp \left\{ -0.5(\omega - \varphi)^T \right\}
\]

About a new input vector \( x_\phi \), the predicted distribution of the output vector is got from the formula (17):

\[
    P(t|\phi, \lambda_{\text{MPE}}, \sigma_{\text{MPE}}^2) = \int P(t|\phi, \sigma_{\text{MPE}}^2)P(\phi|\lambda_{\text{MPE}}, \sigma_{\text{MPE}}^2)d\phi
\]

Gauss kernel function is widely used because of its excellent nonlinear data processing performance. This function is usually as follows, where \( \theta \) is kernel width.

\[
    K_G(x, x_i) = \exp \left( -\frac{\|x - x_i\|^2}{2\theta^2} \right)
\]

The multinomial core function is proved to be a valid complement to the Gaussian kernel function, which can be expressed as:

\[
    K_p(x, x_i) = \left[ x_i^T x + 1 \right]^m
\]

Among them, the \( m \) is degrees. The kernel functions of the MKRVM algorithm used in this paper are mainly composed of the above two basic kernel functions and are used to predict the life of capacitive RF-MEMS switches, multiple kernels can be defined as:

\[
    K(x, x_i) = \sum_{j=1}^t v_j K_G(x, x_i) + \sum_{r=1}^u v_r K_p(x, x_i)
\]

where the \( v_j \) represents the weights of the \( j \) Gaussian kernel function and the \( v_r \) represents the \( r \) polynomial kernel function, \( \sum_{j=1}^t v_j + \sum_{r=1}^u v_r = 1 \), this paper, \( L=5, U=3 \).

However, the weight of kernel function is easy to affect the speed and accuracy of prediction, so this paper uses DE-QPSO algorithm to find the best weight of kernel function in MKRVM.

The article uses root mean square as a Health Indicator (HI), defined as follows, where \( v_i \) is the \( i \) lifetime characteristic data.

\[
    HI = \frac{1}{k} \sqrt{\sum_{i=1}^k v_i^2}
\]

4. EXPERIMENTAL TEST AND ANALYSIS

In this experiment, the switching life test is carried out under the requirement of low threshold voltage drive. The beam of the switch is selected as metal aluminum, beam length is 200μm, beam width 30μm,
beam thickness 1 μm, the distance between plates is 2 μm, transmission line width is 150 μm, the dielectric material is aluminum nitride. The applied bias voltage selects the pulse waveform bias voltage [10]. In order to ensure the accuracy of the final forecast, at last, 581 sets of data were obtained for continuous data processing and prediction.

This experiment uses two life prediction methods to predict the switching life, RVM and MKRVM respectively. Set the polynomial kernel function order to 1, 2, 3, and the width factor of the Gaussian kernel function to 0.1, 0.2, 0.3, 0.4, 0.5 respectively. The prediction results are shown in Fig. 3:

![Fig. 3. Comparison of different life prediction methods](image)

![Fig.4. Error of two prediction algorithms](image)

We use the two methods to obtain the results of life prediction and the absolute error of the actual data to make a comparison, error the definition is as shown in formula (22):

\[
\text{error} = \frac{|D_{\text{real}} - D_{\text{pre}}|}{D_{\text{real}}} \tag{22}
\]

We can get the following conclusion from Fig.3 and 4: the absolute error of the switching life predicted by the MKRVM algorithm is smaller, which is closer to the real data obtained by is closer to the real data obtained by the experiment (the original data in the figure represents the data after denoising), so the prediction results obtained by using the multi-core learning method are more accurate than the results obtained by the single-core learning method.

It can be seen from the prediction time of the two methods that the MKRVM algorithm takes 0.21 s and the RVM algorithm takes 0.63 s, which is faster than the RVM algorithm. On the other hand, we use the formula (21) to obtain

| Method | Raw Data | MKRVM | RVM |
|--------|----------|-------|-----|
| HI (s) | 3.0657e+06 | 3.1043e+06 | 3.1961e+06 |

| Method | MKRVM | RVM |
|--------|-------|-----|
| Forecast time(s) | 0.21 | 0.63 |

the life data predicted by each method to calculate the health index, and the results are shown in Table 6. From Table 6 MKRVM it can be seen that the health index of the predicted results is 3.1043e+06 s, which is closer to the health index 3.0657e+06 s of the original life data, and the RVM is 3.1961e+06 s. To sum up, by comparing the accuracy, running time and health index. This paper chooses MKRVM to predict the life of capacitive RF-MEMS switch.

Through the prediction of the residual life of capacitive RF-MEMS switch, it can be concluded that when the elastic coefficient of switch is between 4-16 N/m, the life of switch is longer. When a switch with an elastic coefficient of 10 is selected, the life span can reach about 1388 hours, then we get the switch RUL of 1300 hours, about 54 days, after continuing to run 50 days, it is necessary to replace
the switch in time to maintain the system to continue normal operation, to ensure the reliability of the system.

5. CONCLUSION
The MKRVM has better learning performance compared with RVM, and the sparse weight of MKRVM is generated by DE-QPSO optimization algorithm. This paper only discusses the influence of elastic coefficient K on the switching life of capacitive RF-MEMS, in the future research, we will continue to study the influence of other factors on its life, further deepen the research on the reliability of MEMS devices, and make the research more comprehensive.

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